Modeling *Aedes Albopictus* population dynamics in southern France using Interpretable Machine Learning

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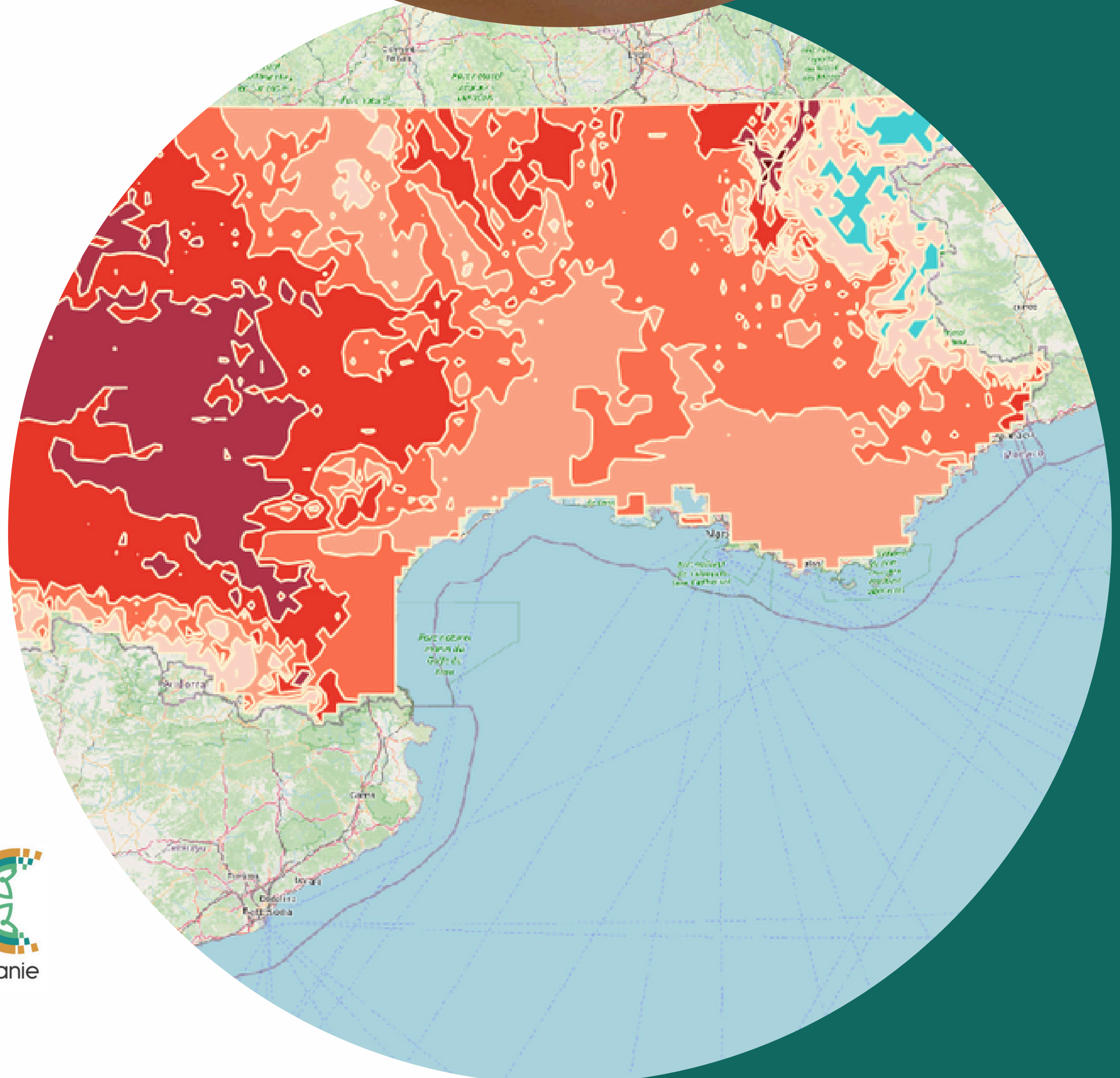
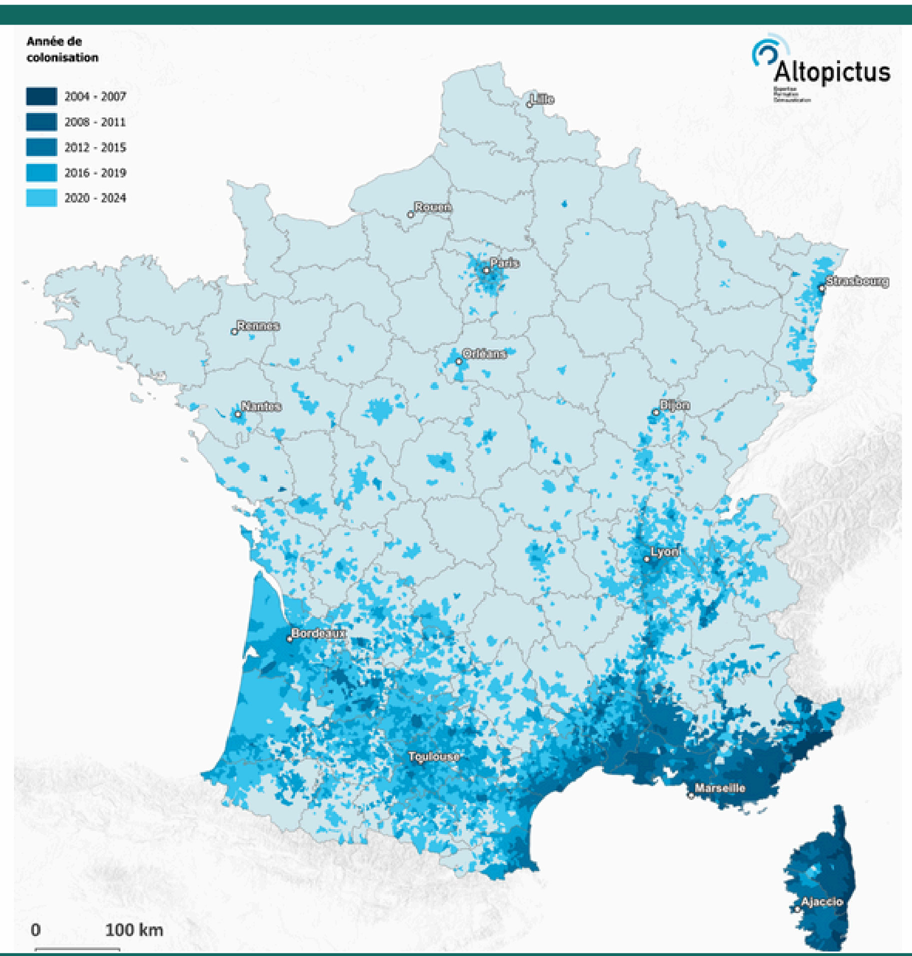
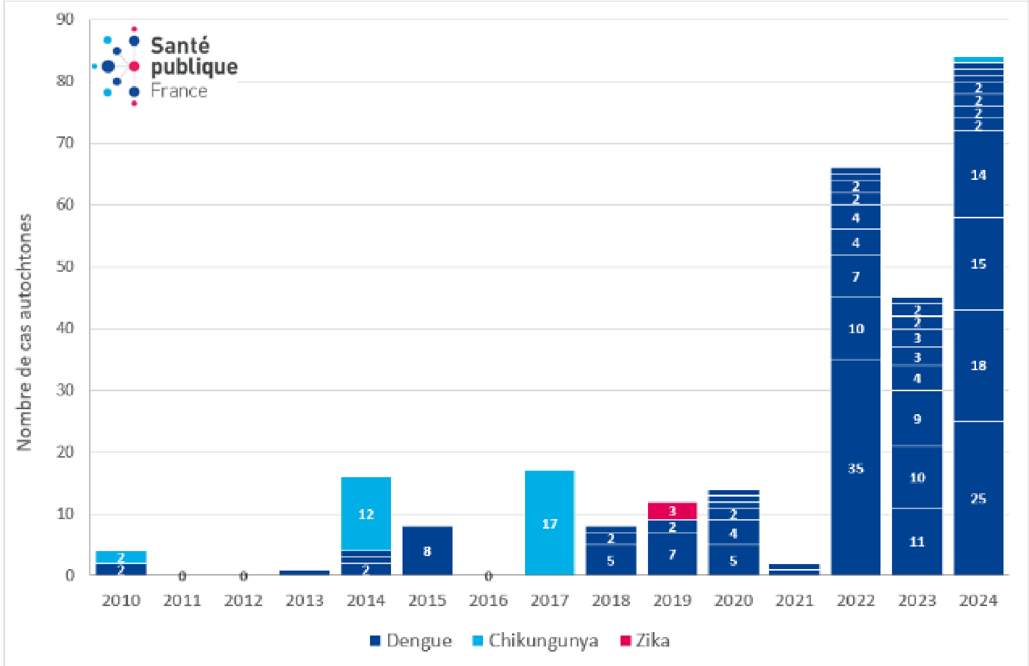
Didier Fontenille (MIVEGEC)



INTRODUCTION





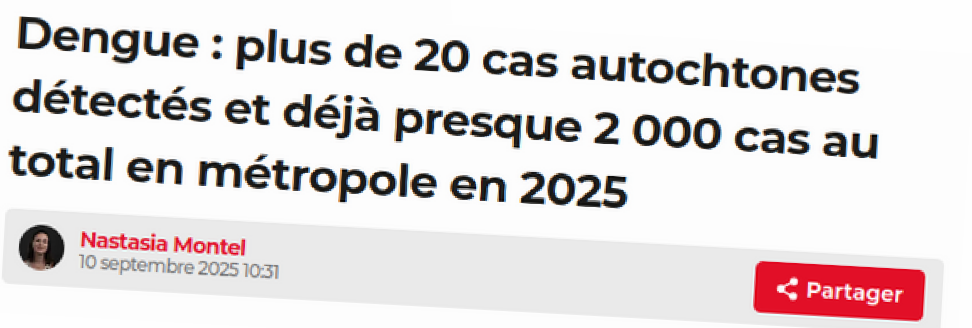
- ***Aedes Albopictus*** **-** vector of several infectious diseases (zika, chikungunya, dengue, …)
- Introduced in hexagonal **France** in **2004**, now present in 84% of the French hexagonal departments (more than 6800 municipalities)
- Endemic zones are expanding their borders
- **2025 : major endemic outbreaks in France**

Endemic outbreaks of *Ae. albopictus*-borne diseases are becoming increasingly common in France


Chikungunya : près de 400 cas autochtones en métropole depuis le début de mai

Si plusieurs épisodes sont désormais clos, l'été 2025 est d'une ampleur inédite en métropole pour les cas autochtones de chikungunya, dont le virus se transmet par des piqûres de moustique tigre.

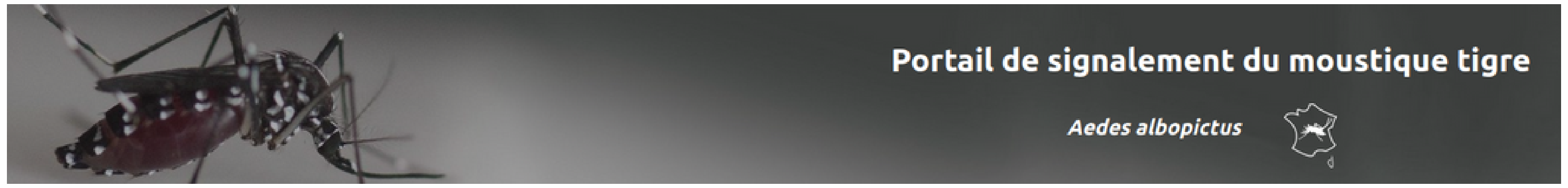
Le Monde avec AFP
Publié aujourd'hui à 12h37 · Lecture 1 min.


Dengue : plus de 20 cas autochtones détectés et déjà presque 2 000 cas au total en métropole en 2025

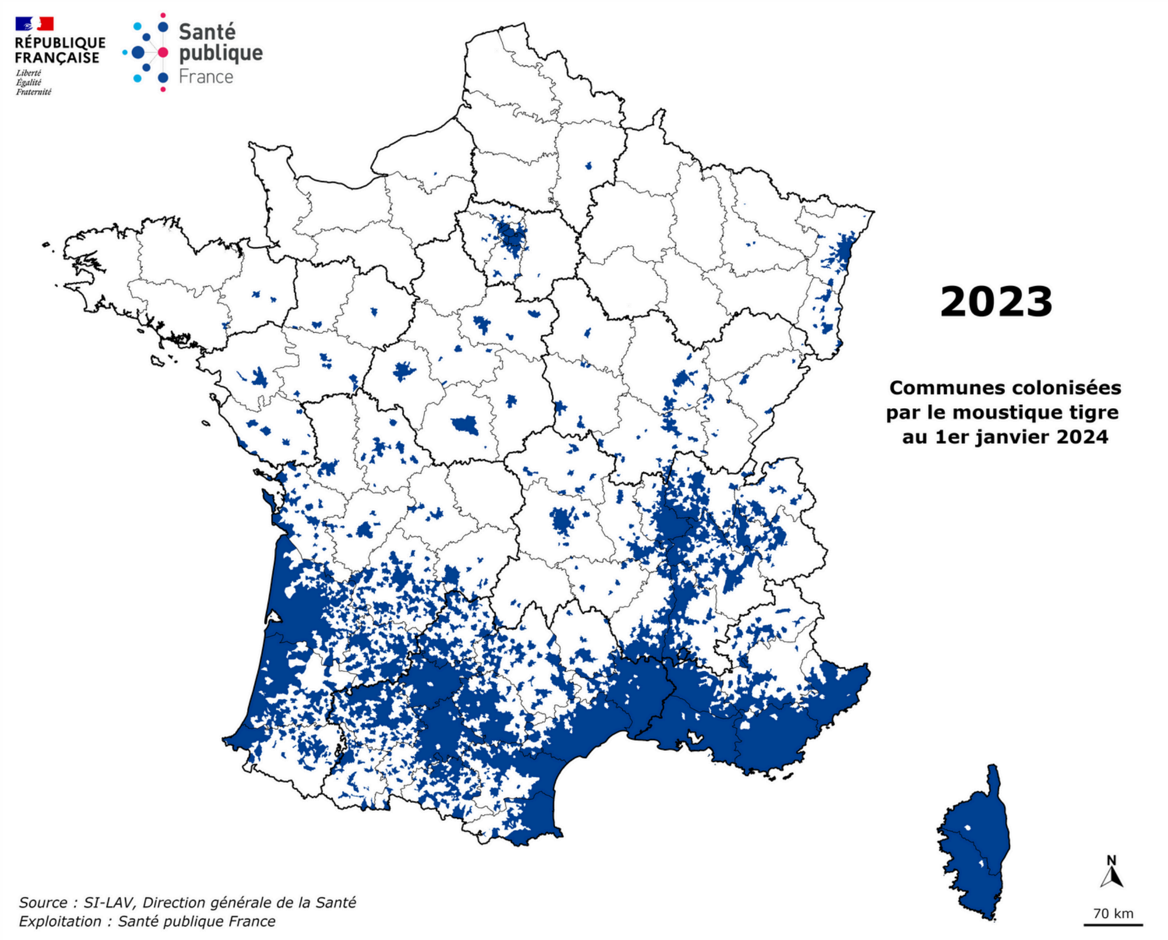
Nastasia Montel
10 septembre 2025 10:31
Partager

Current information on *Ae. Albopictus* distribution in France remains limited

Citizen surveillance



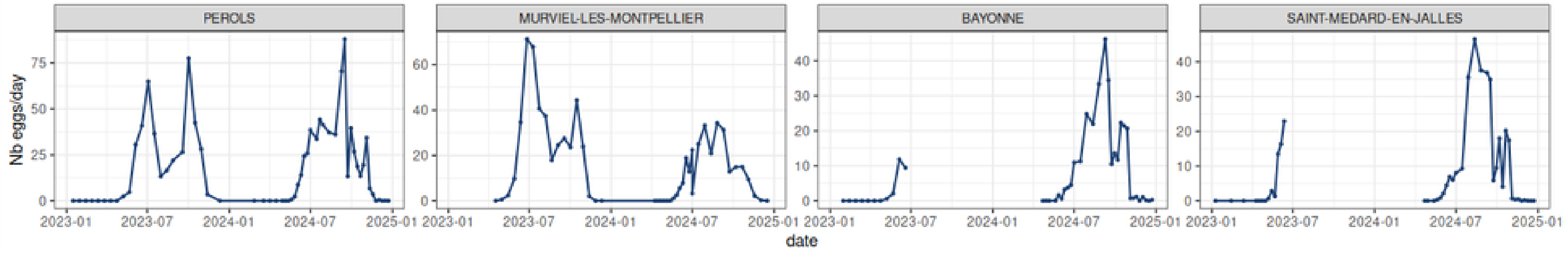
anses



Field surveillance in sample sites

Altopictus
Expertise
Formation
Démoustication

EID MÉDITERRANÉE



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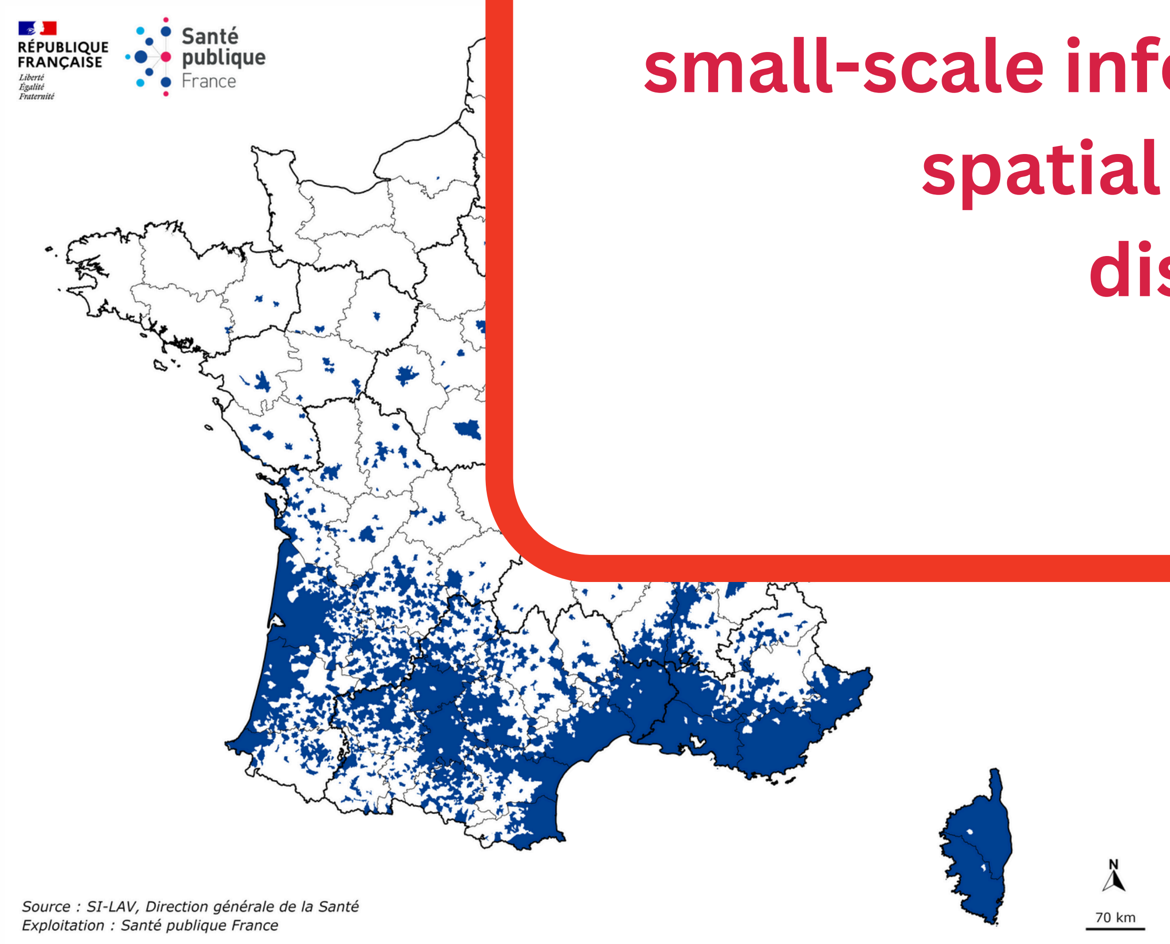

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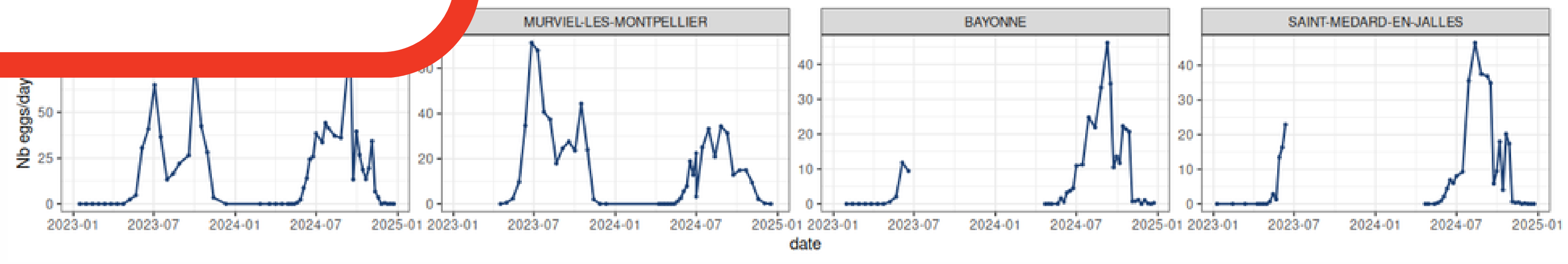
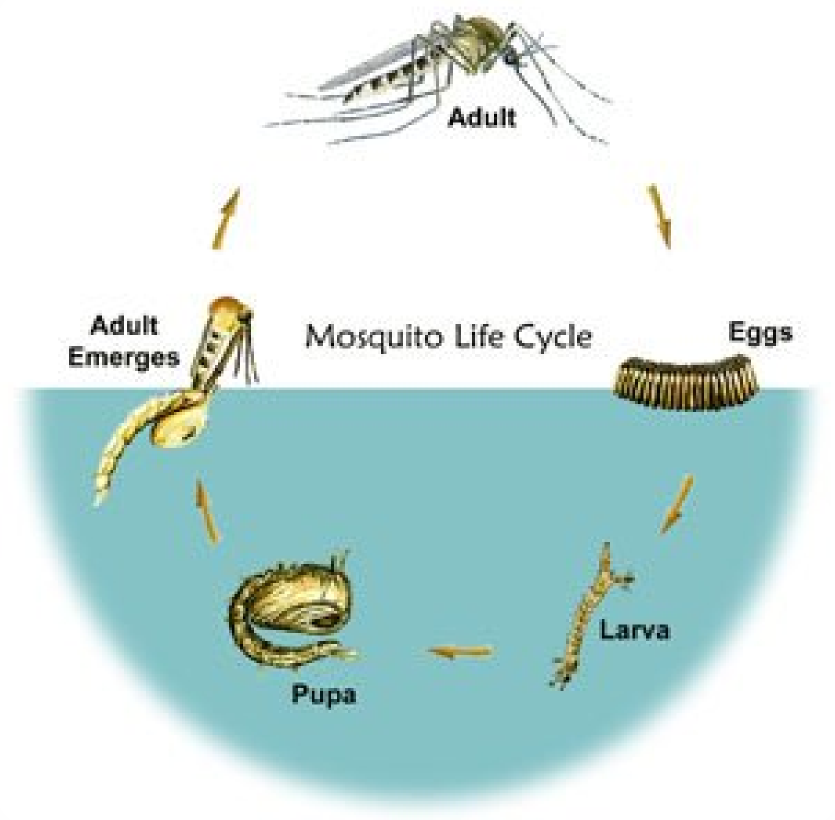
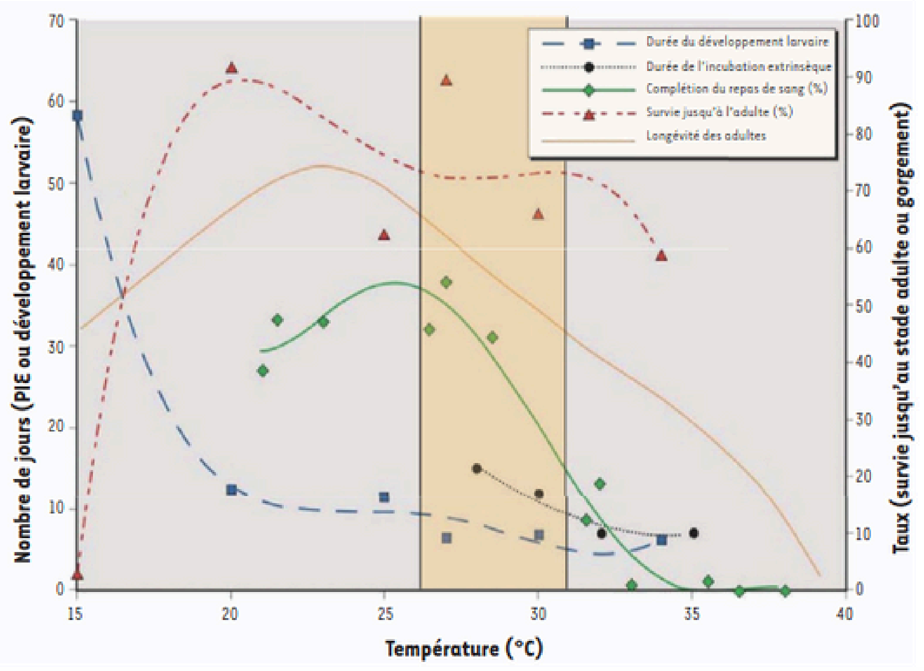


But no real-time, wide coverage, small-scale information on mosquito spatial and temporal distribution

Current knowledge on weather - mosquito association in France remains limited



epa.gov



Dupuis et al. 2025

- **Ectotherm:** life stages are strongly influenced by climatic conditions (e.g. temperature, rainfall, etc.)
- Theoretical response of mosquito life cycle to weather well documented in lab conditions
- **But *Ae. Albopictus* shows high ecological plasticity across environments**

> In newly colonized areas, the link between weather and mosquito dynamics remains limited

Objectives of the study

1. Identify weather determinants of *Ae. Albopictus* dynamics in southern France

which will help in..

- Improving our knowledge of *Ae. Albopictus* local biology
- Studying the causes of shifts in seasonal activity

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2. Predict and forecast *Ae. Albopictus* distribution in real time and at operational scales

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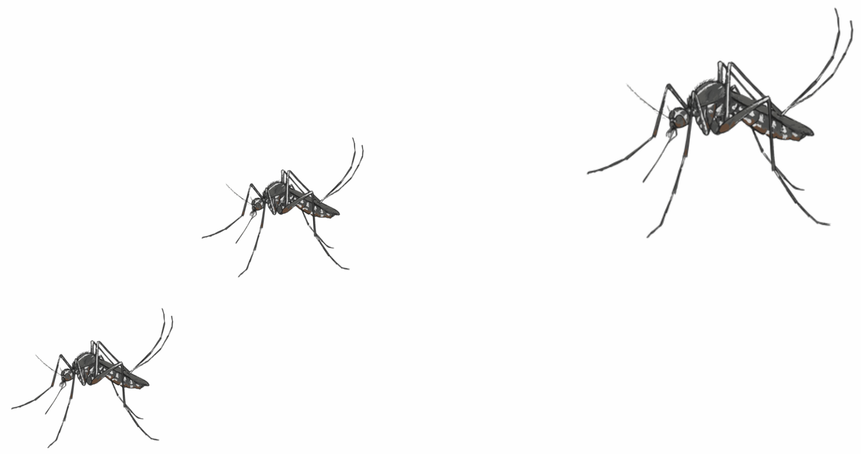
- **Studying the causes of shifts in seasonal activity**

which will help in..

- **Better anticipating the nuisance and health risk**
- **Optimizing mosquito control resources**



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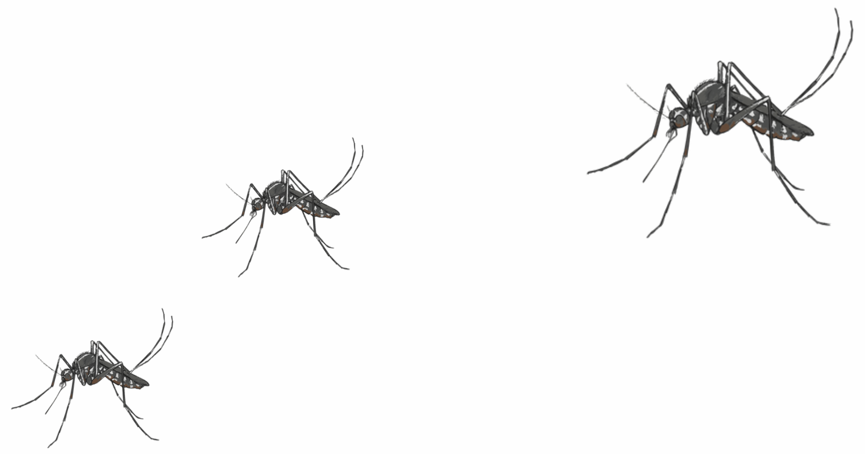

IA and explainable IA

MATERIALS & METHODS

Entomological data

2 years continous surveillance (2023 and 2024)
4 sites in southern France (urban residential areas)
(bi-)weekly collection of ovitraps

Altopictus
Expertise
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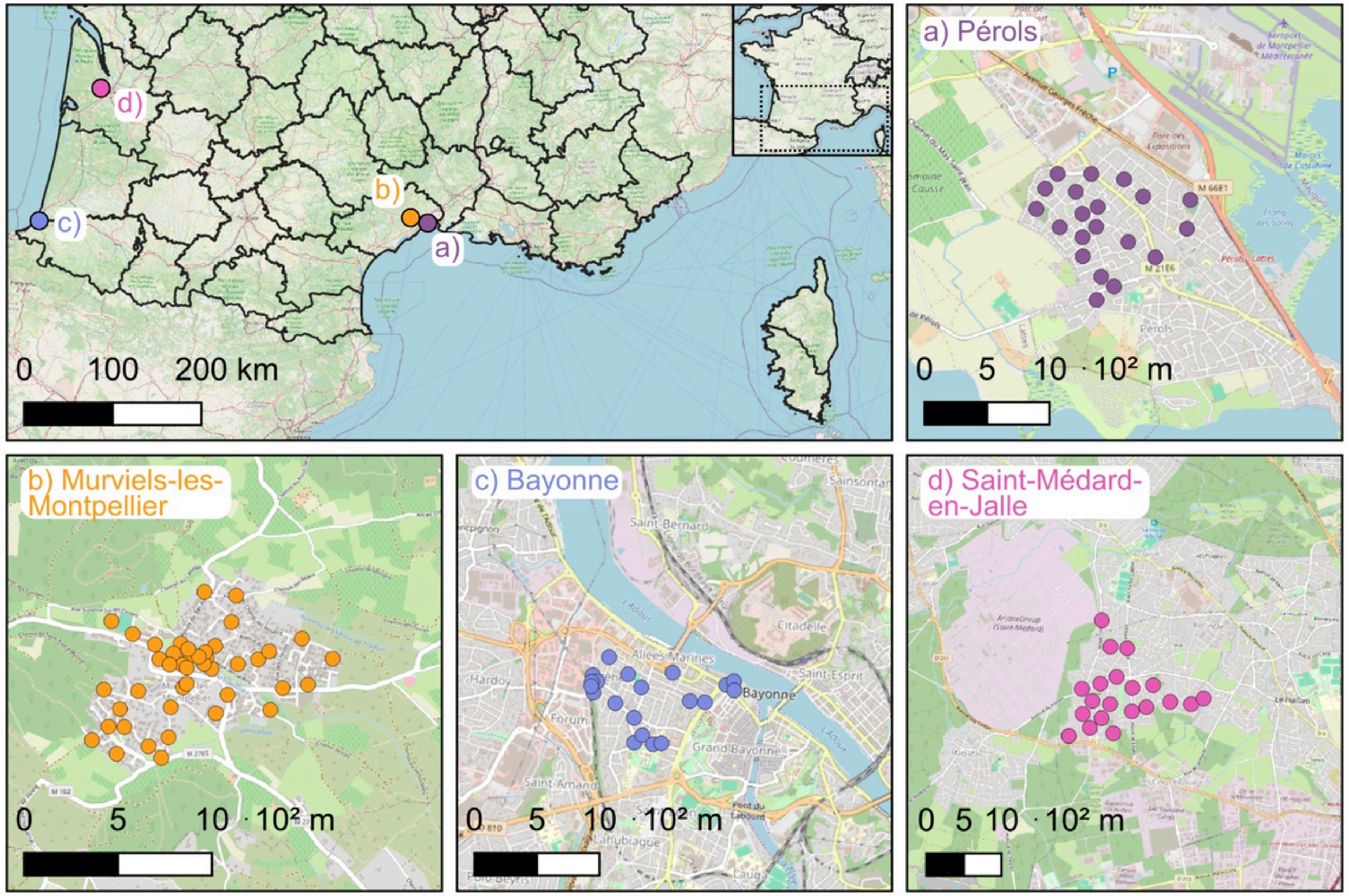

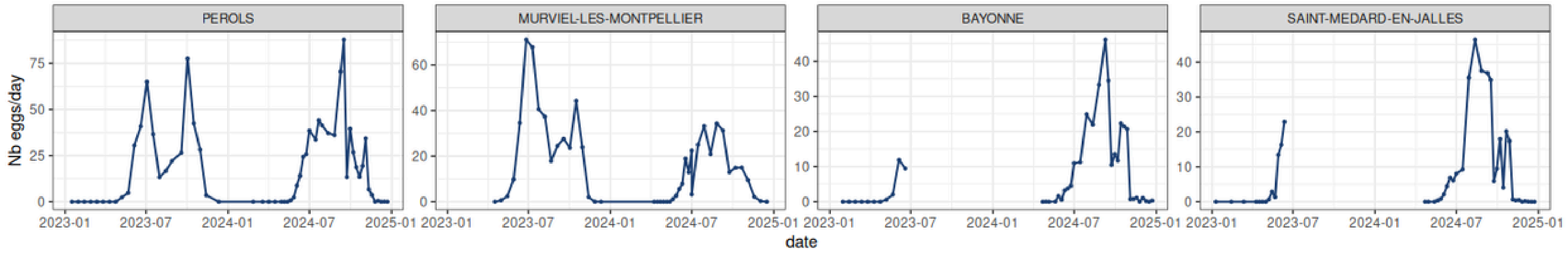

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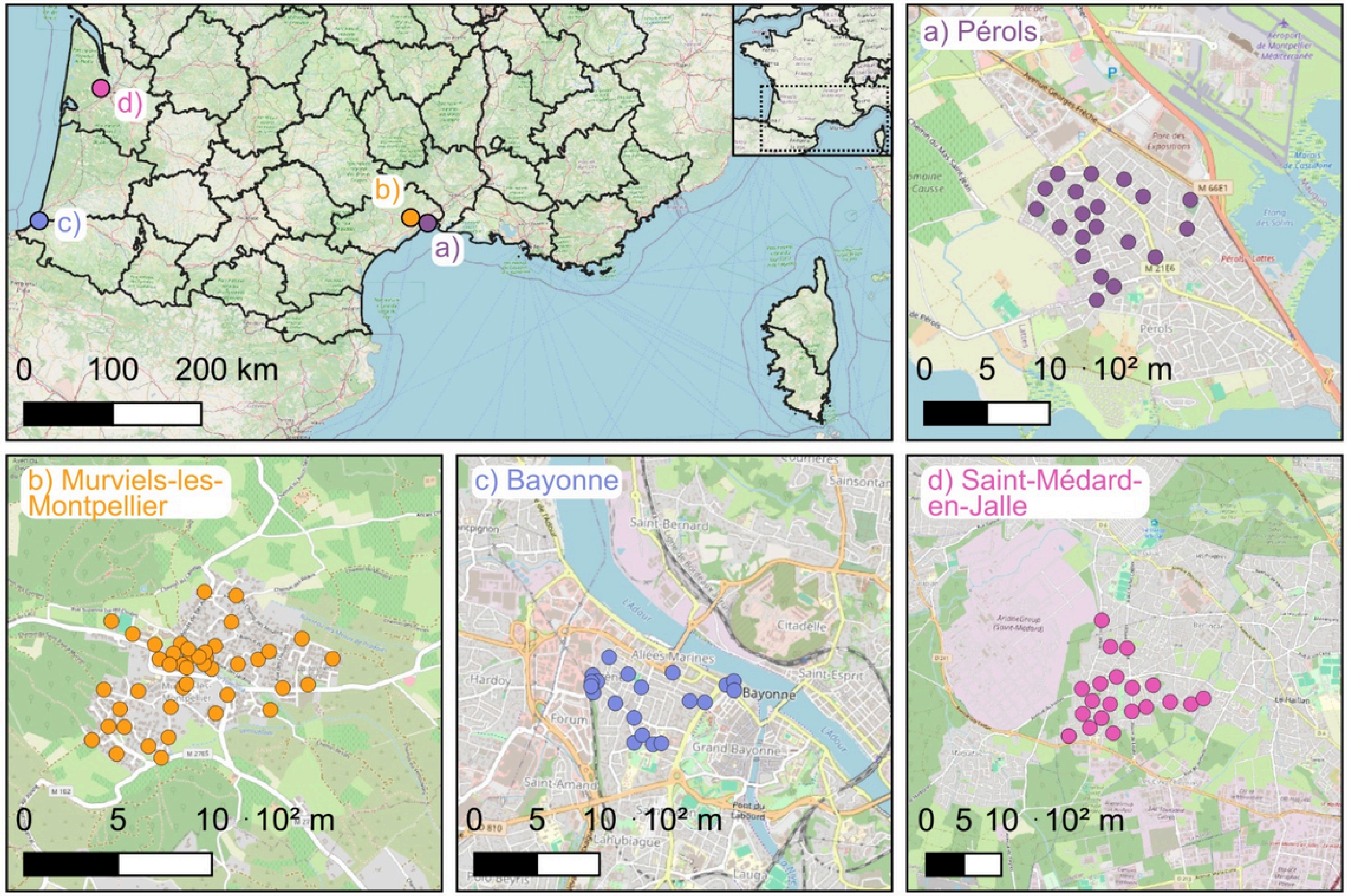
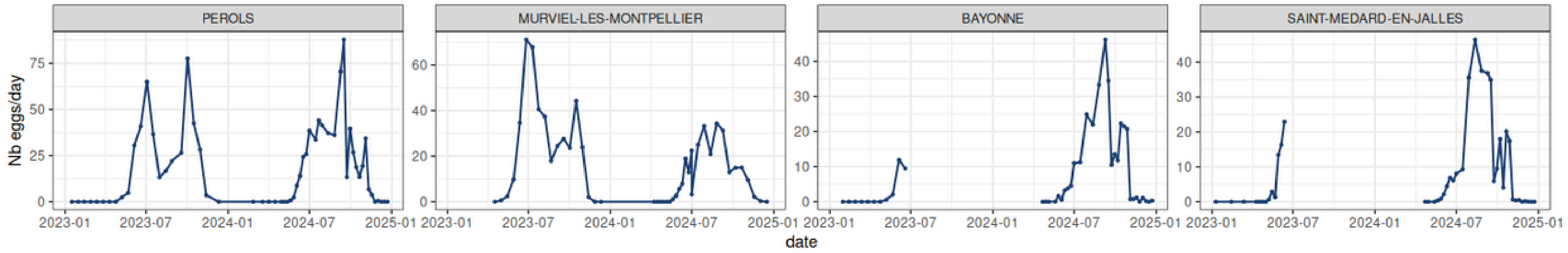
Weather data

Météo France
(daily temperature, precipitation, humidity, wind)

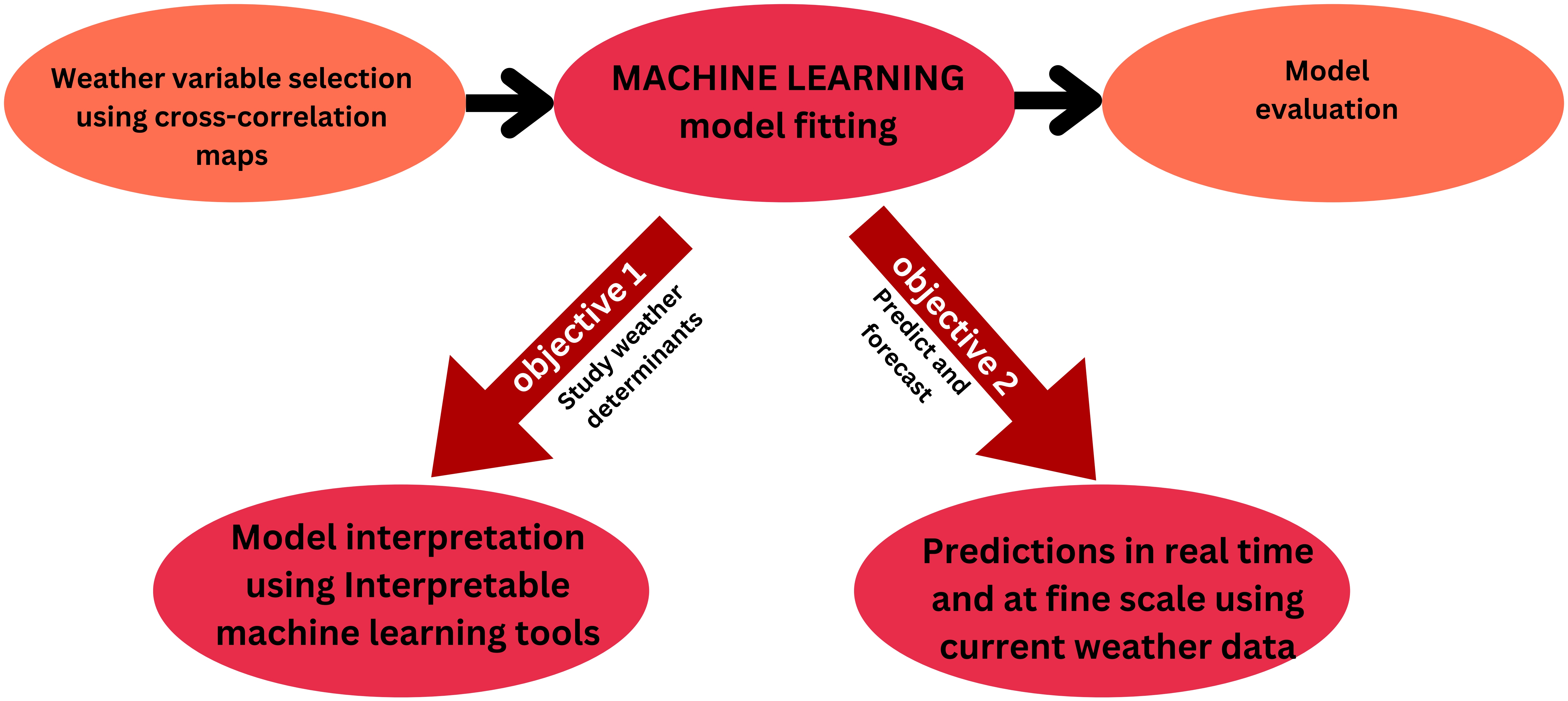
METEO FRANCE
Open Data



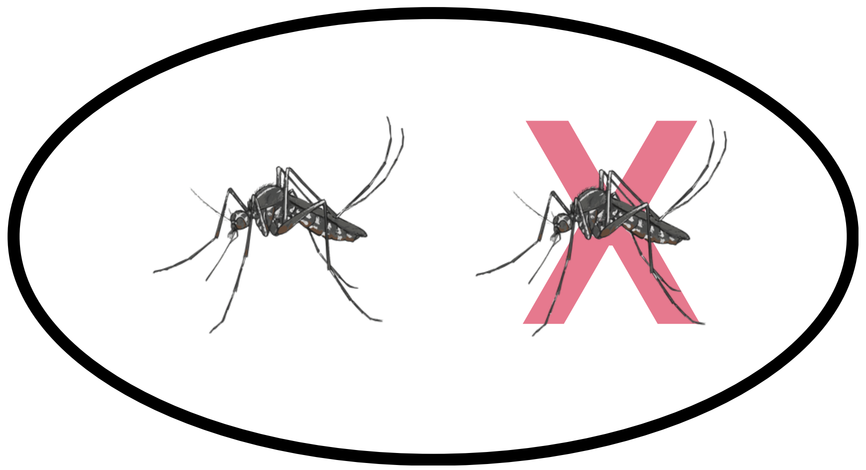


Data modeling pipeline

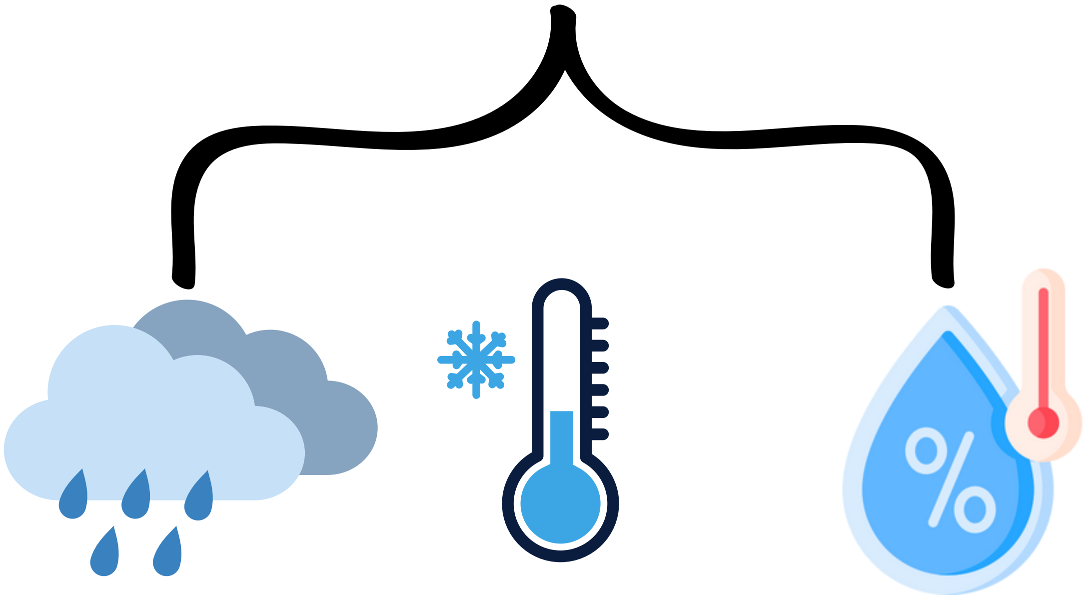
Entomological data + Weather data



2 models



Presence/absence model



Weather determinants are not necessarily the same

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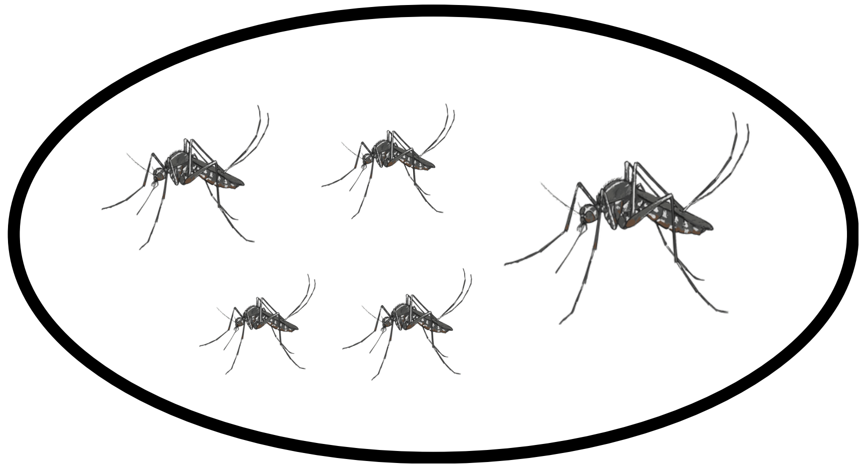
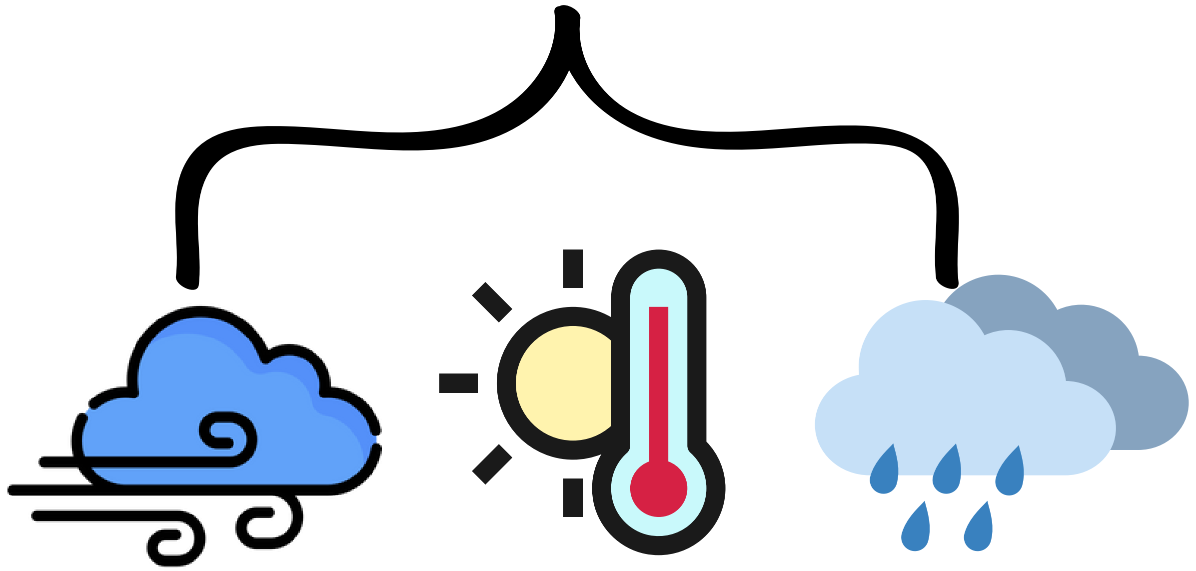
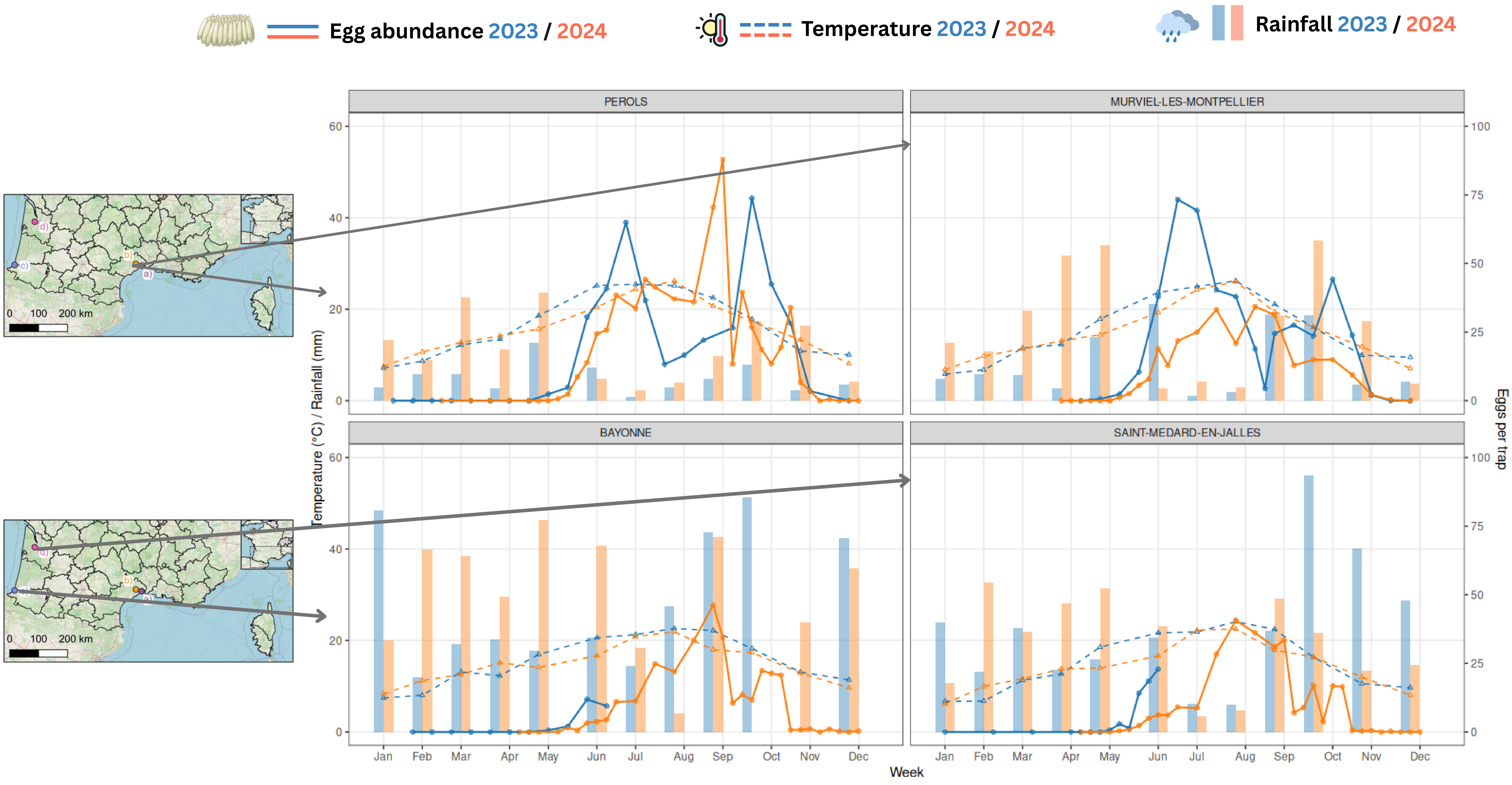


Abundance model



RESULTS

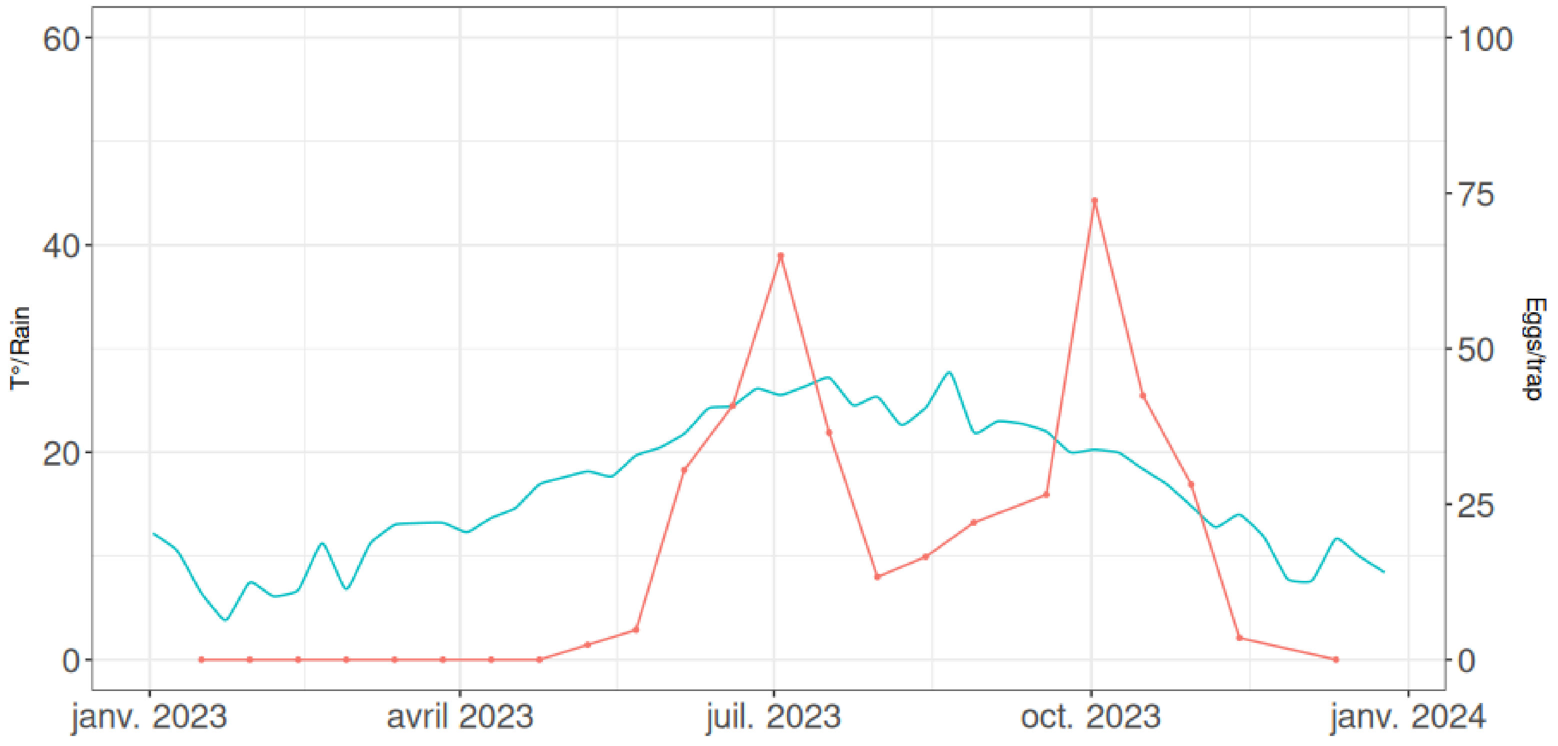
Results : entomological collections



Data-driven variable selection with cross-correlation maps (CCM)

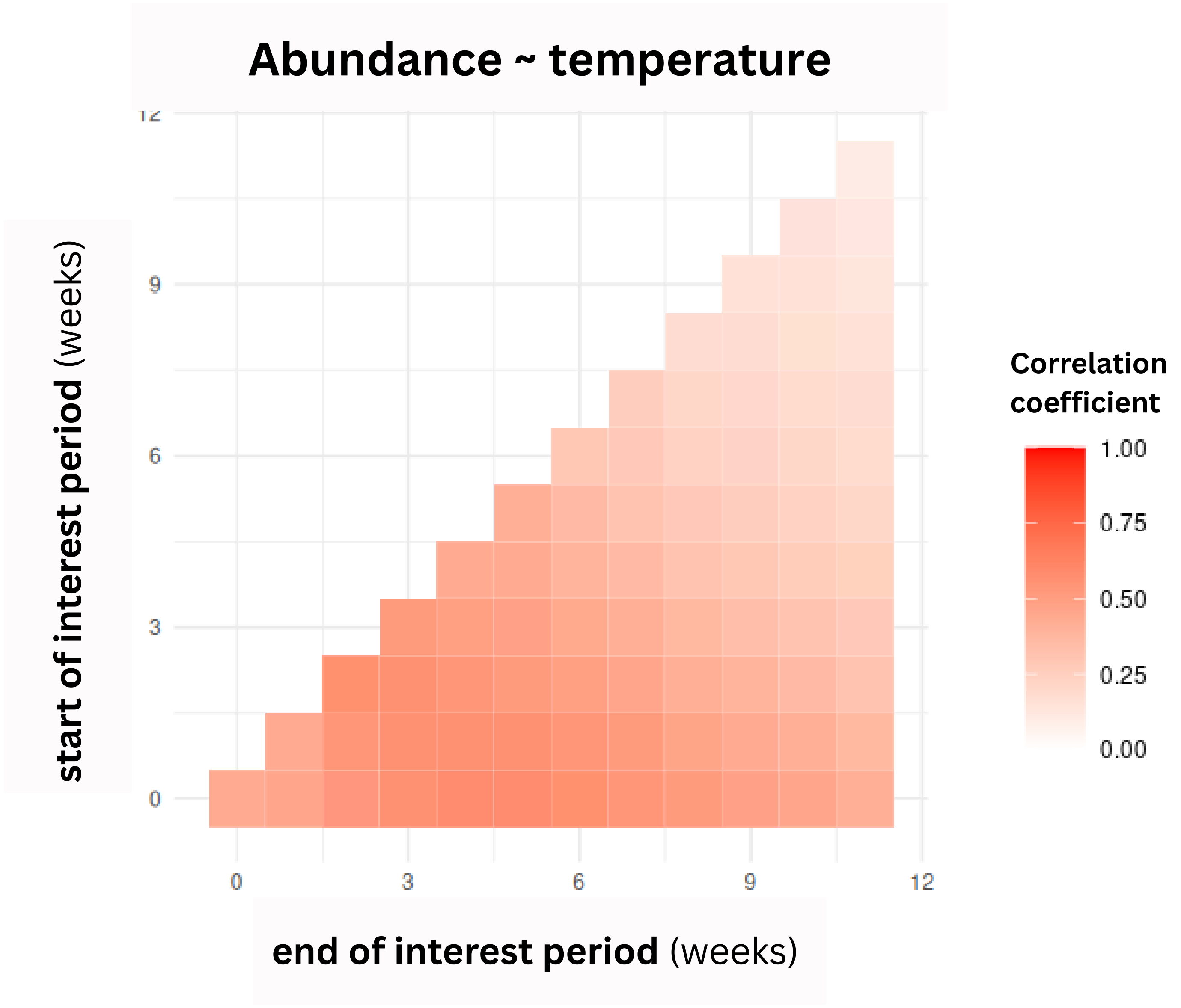
CCM = Tool to visualize <u>delayed (lagged) correlations</u> between two eco-biological time series, such as <u>temperature</u> and <u>mosquito abundance</u>

Curriero et al., 2005. Cross correlation maps: a tool for visualizing and modeling time lagged associations



Egg abundance time series

Temperature time series



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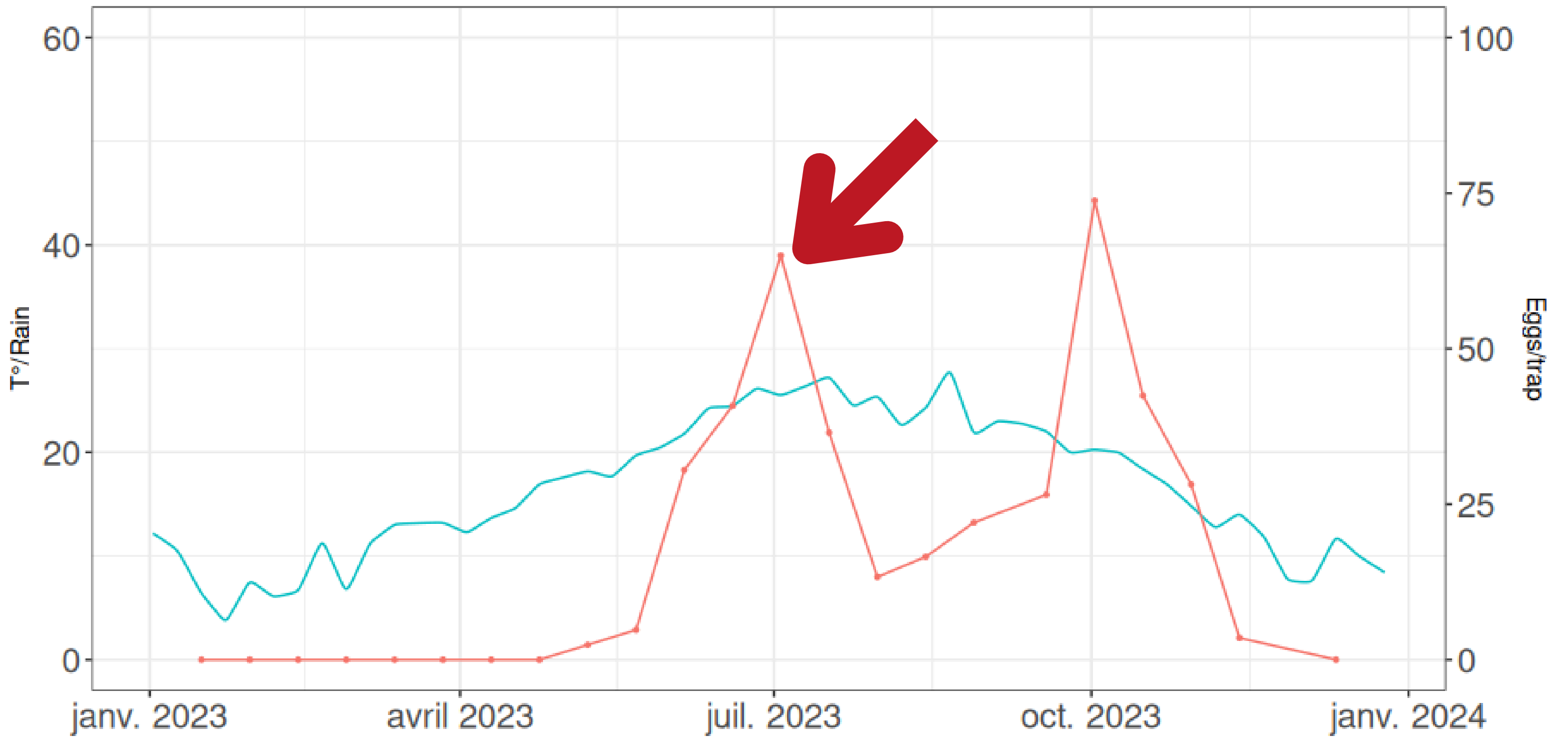

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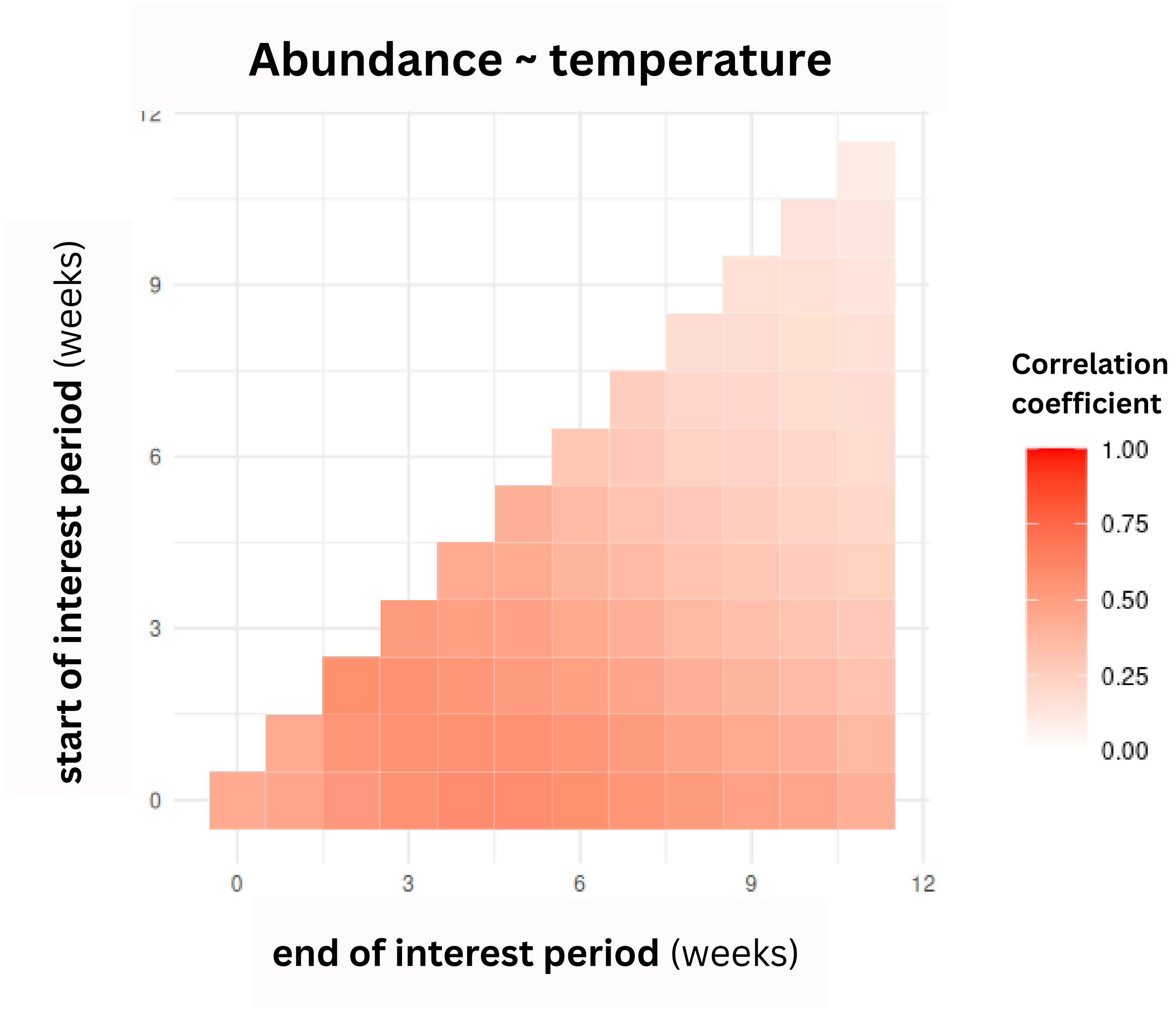

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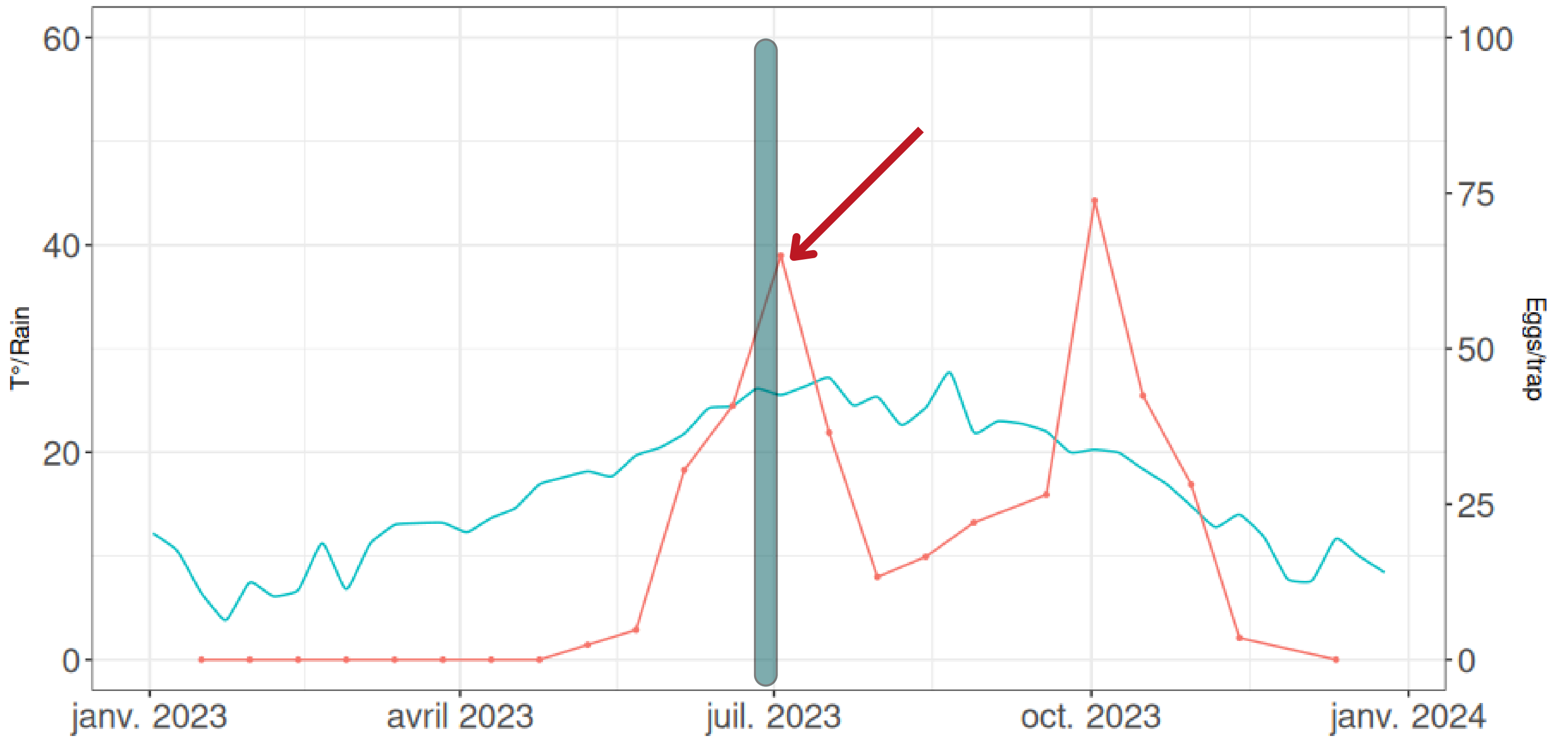

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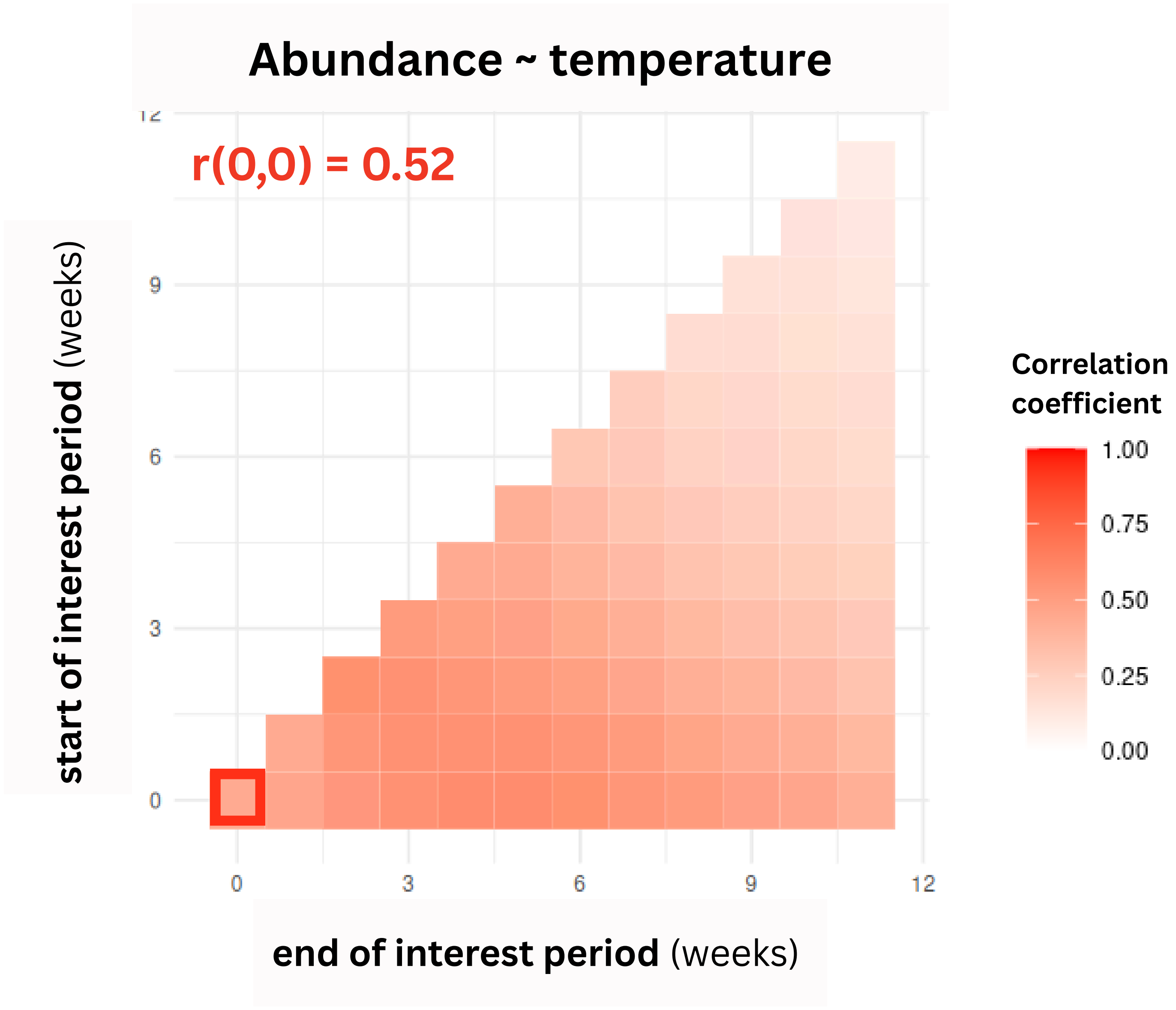

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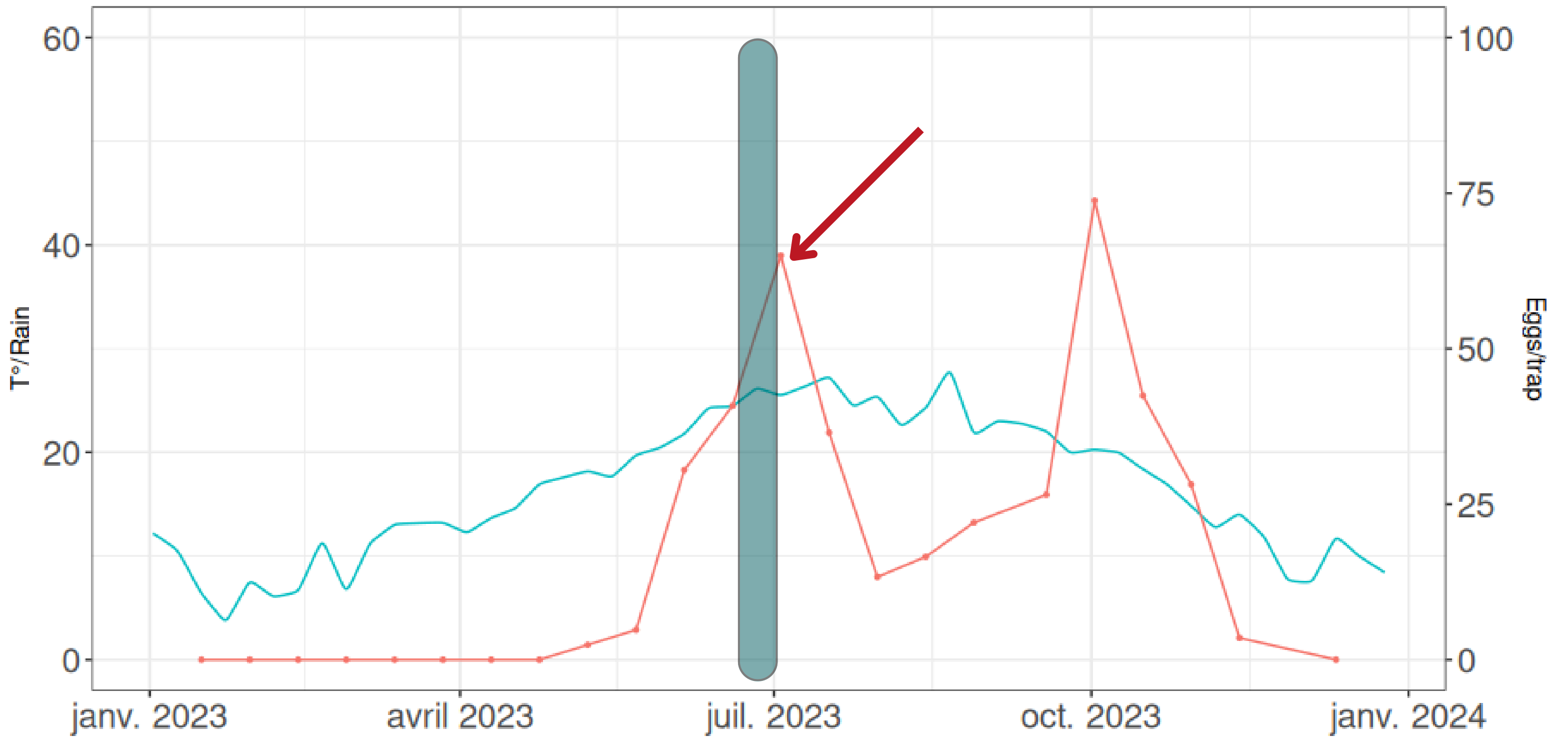

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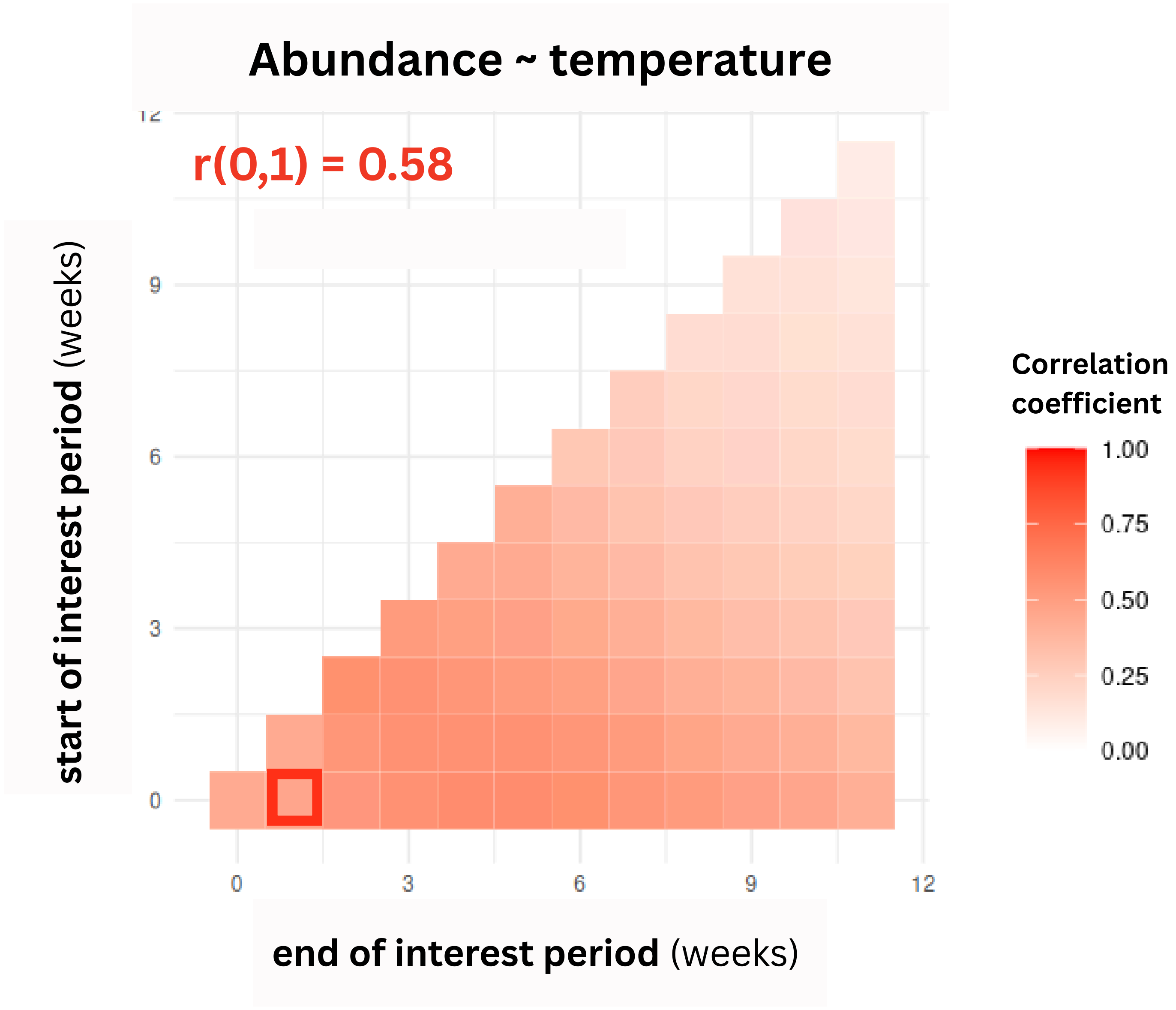

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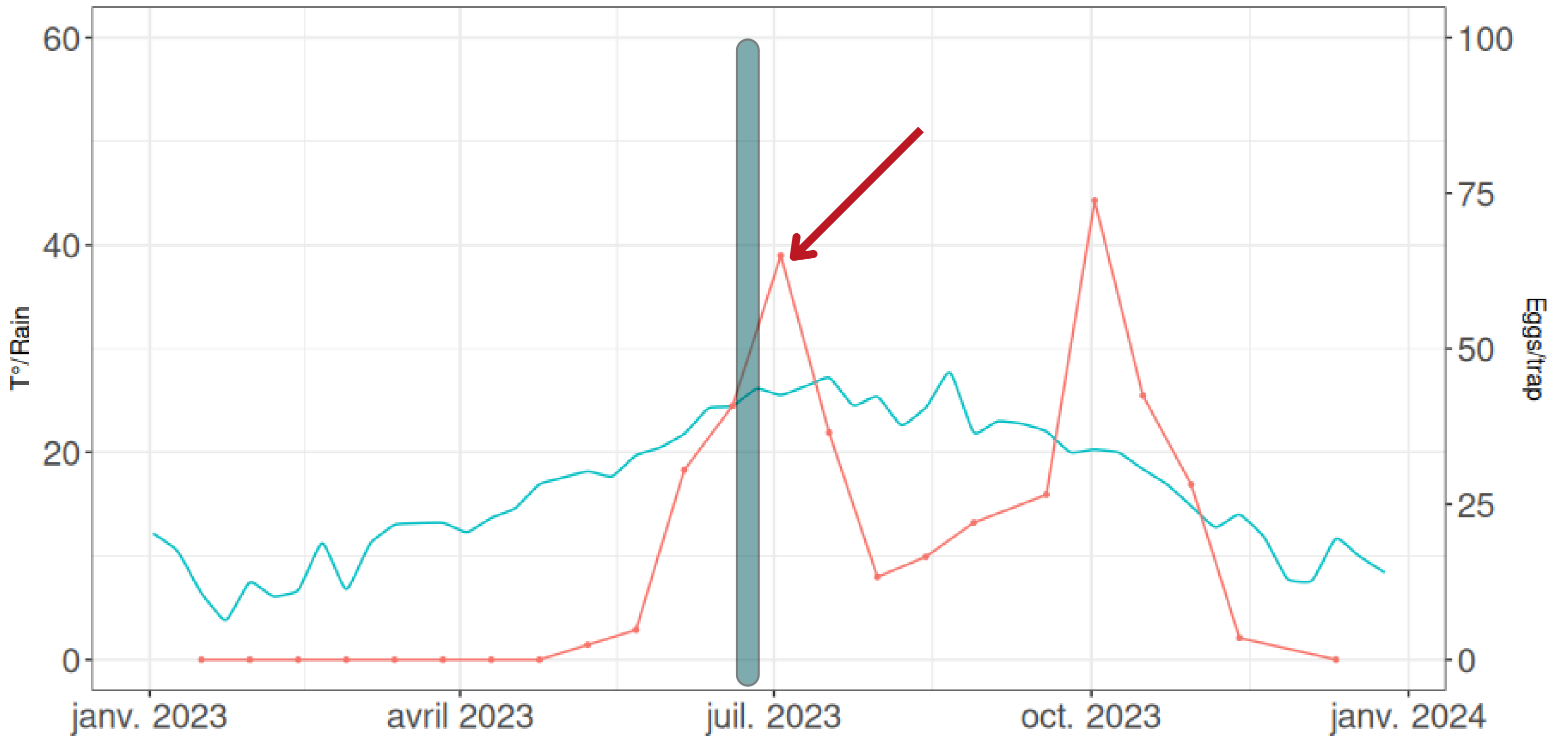

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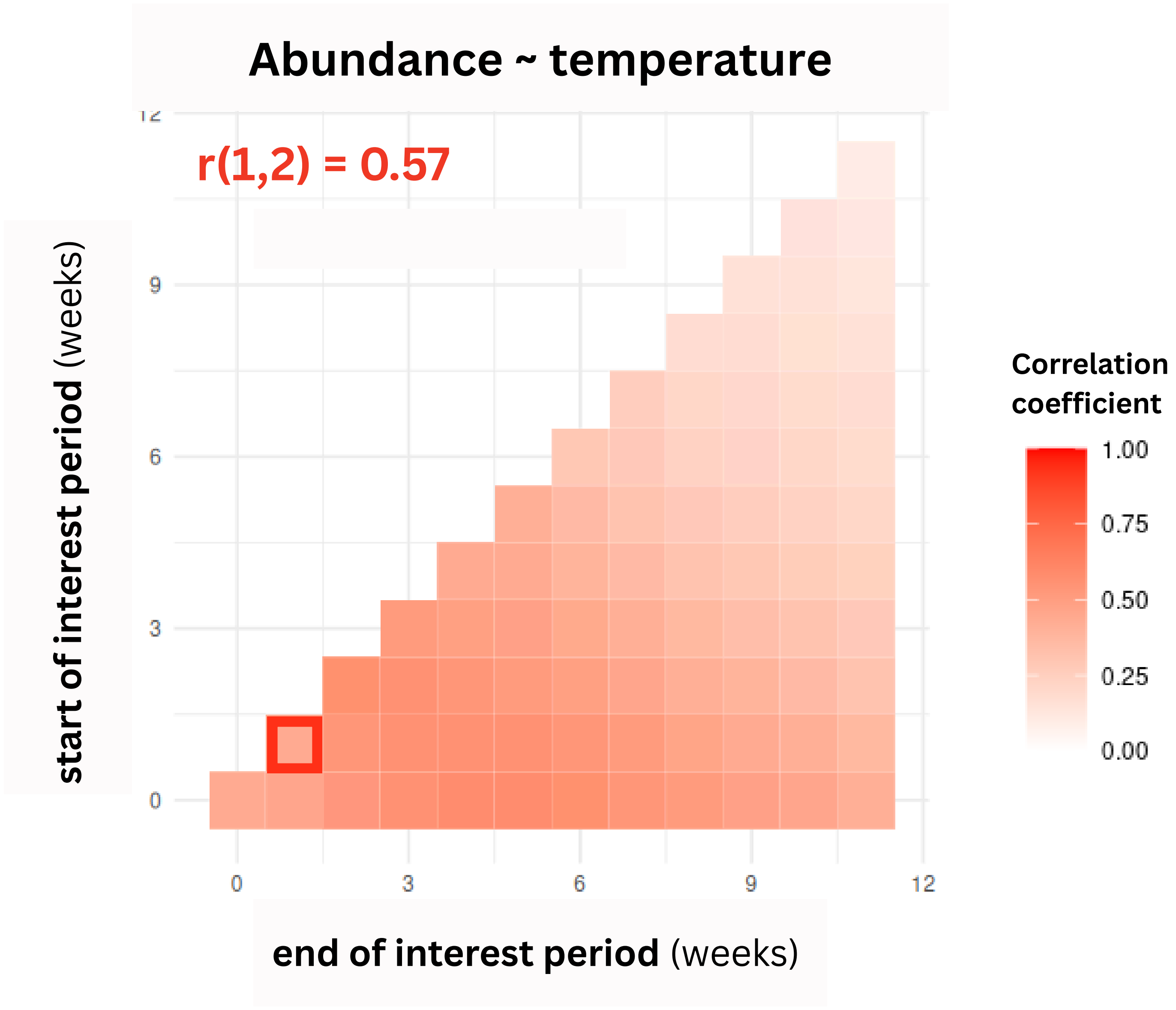

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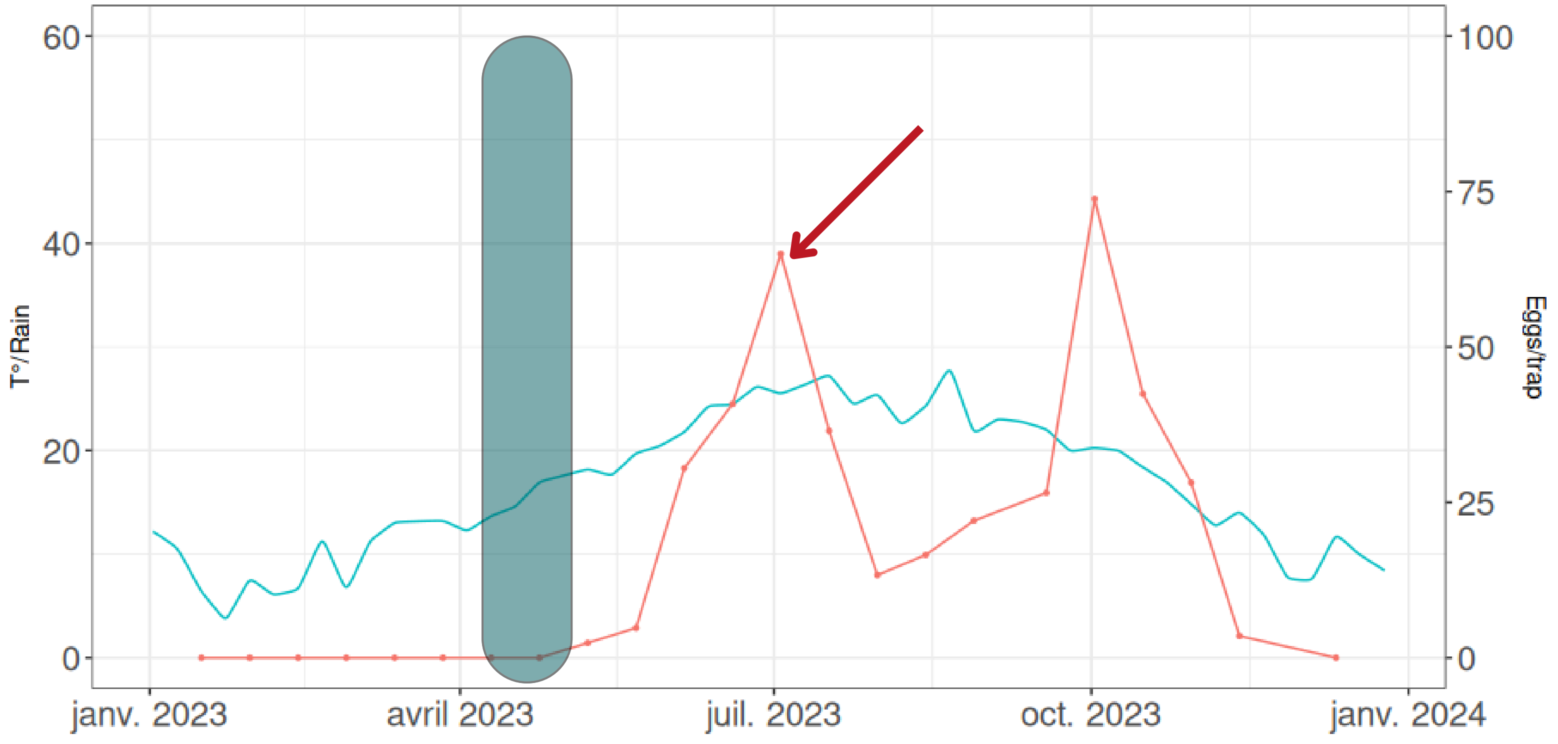

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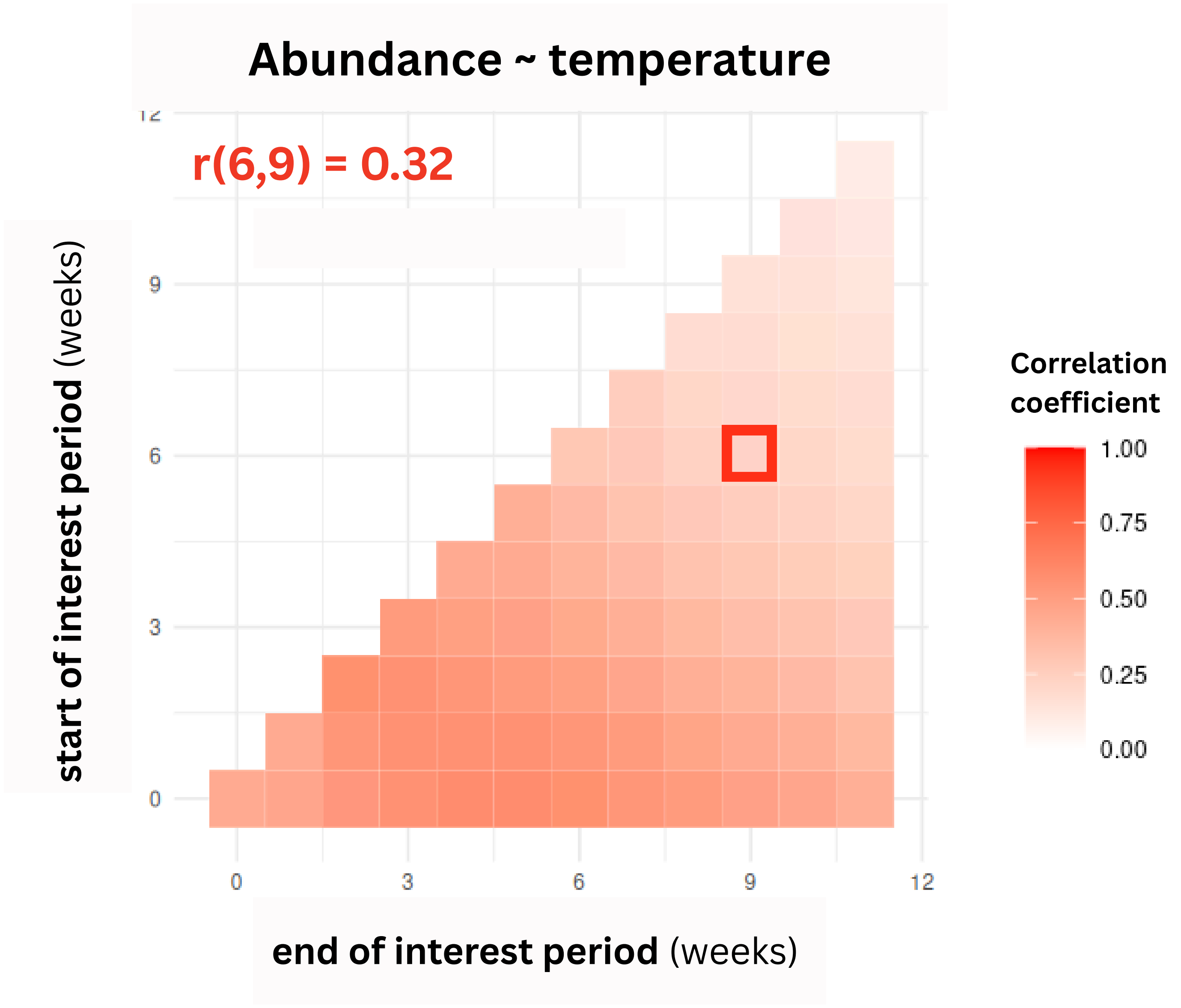

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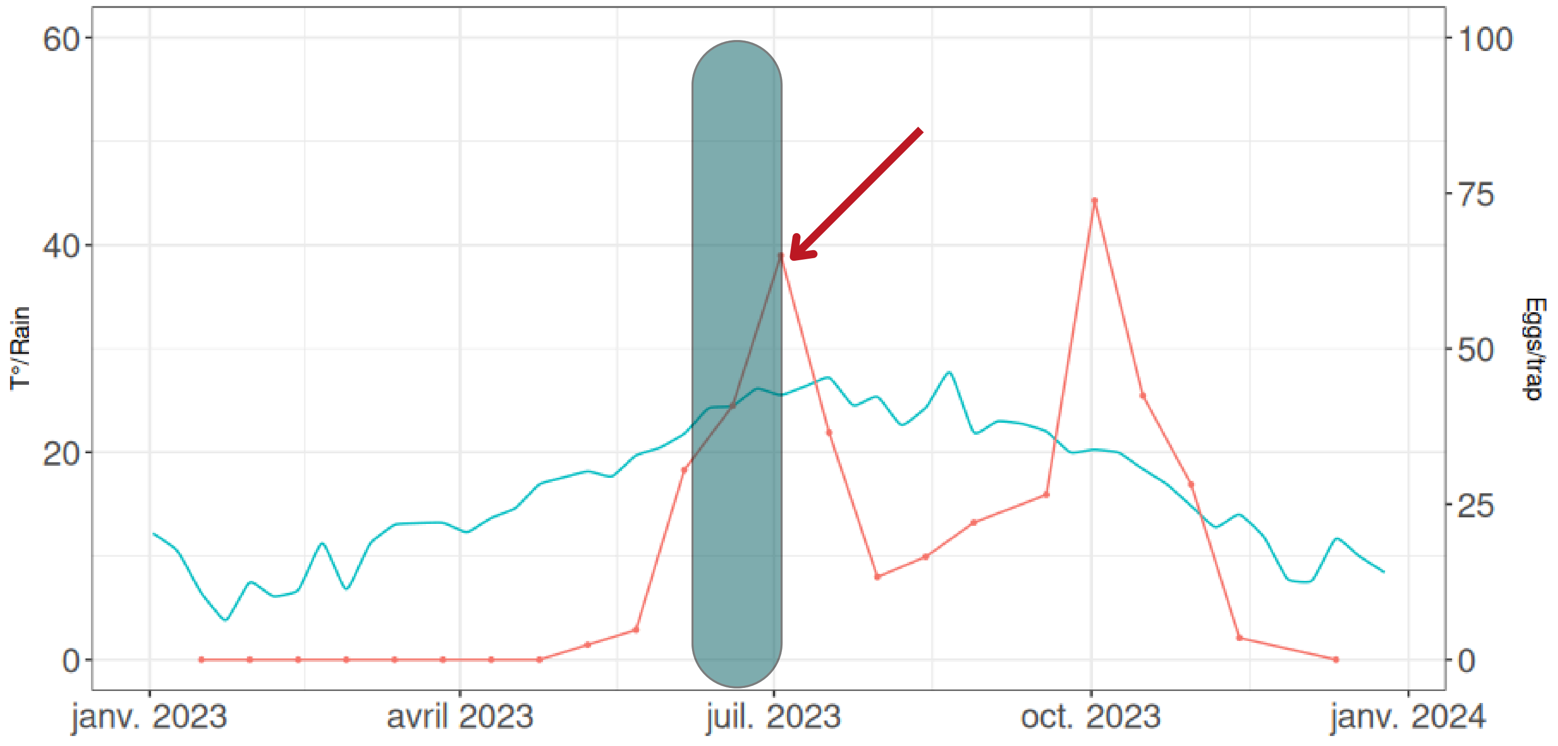

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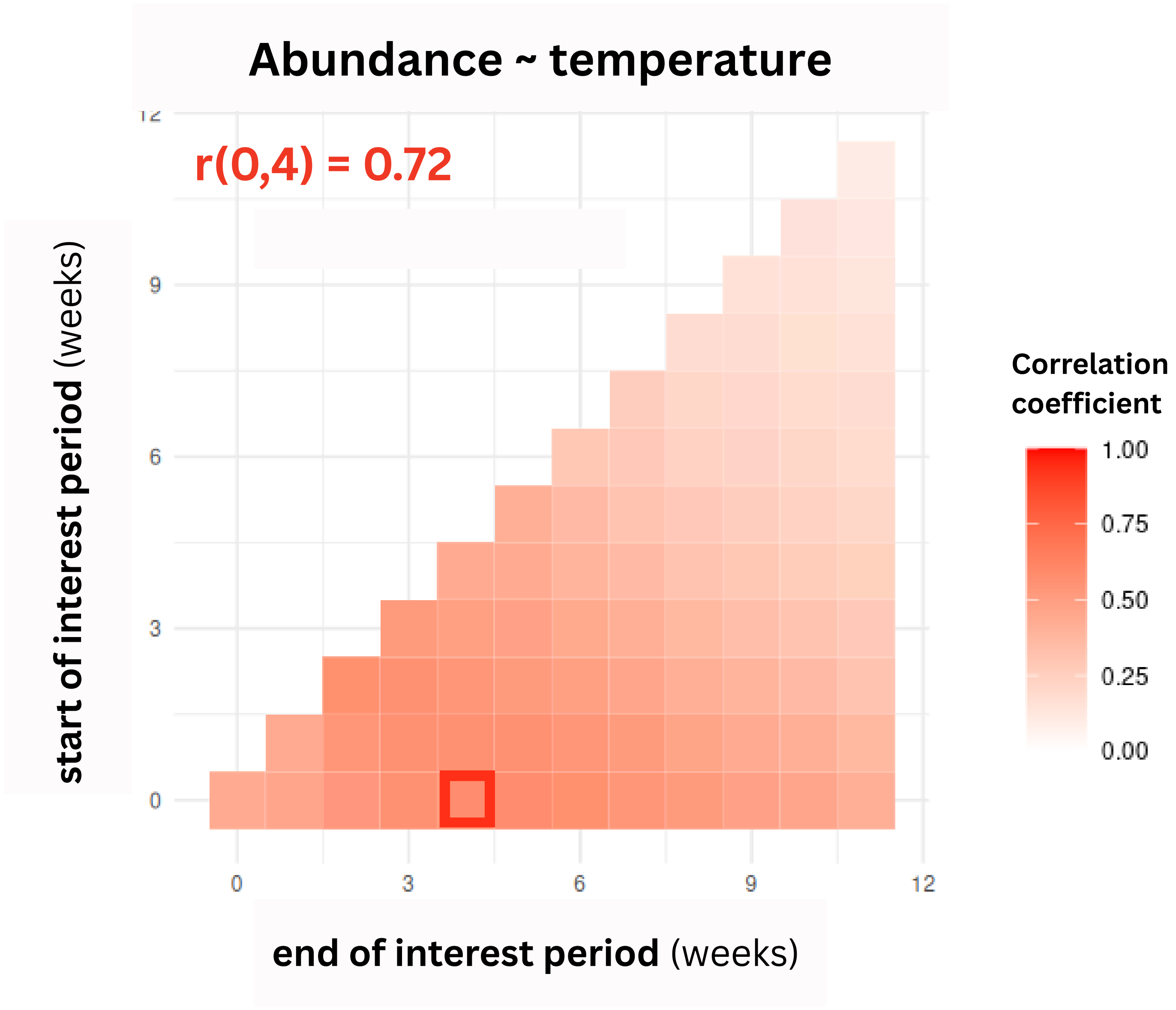
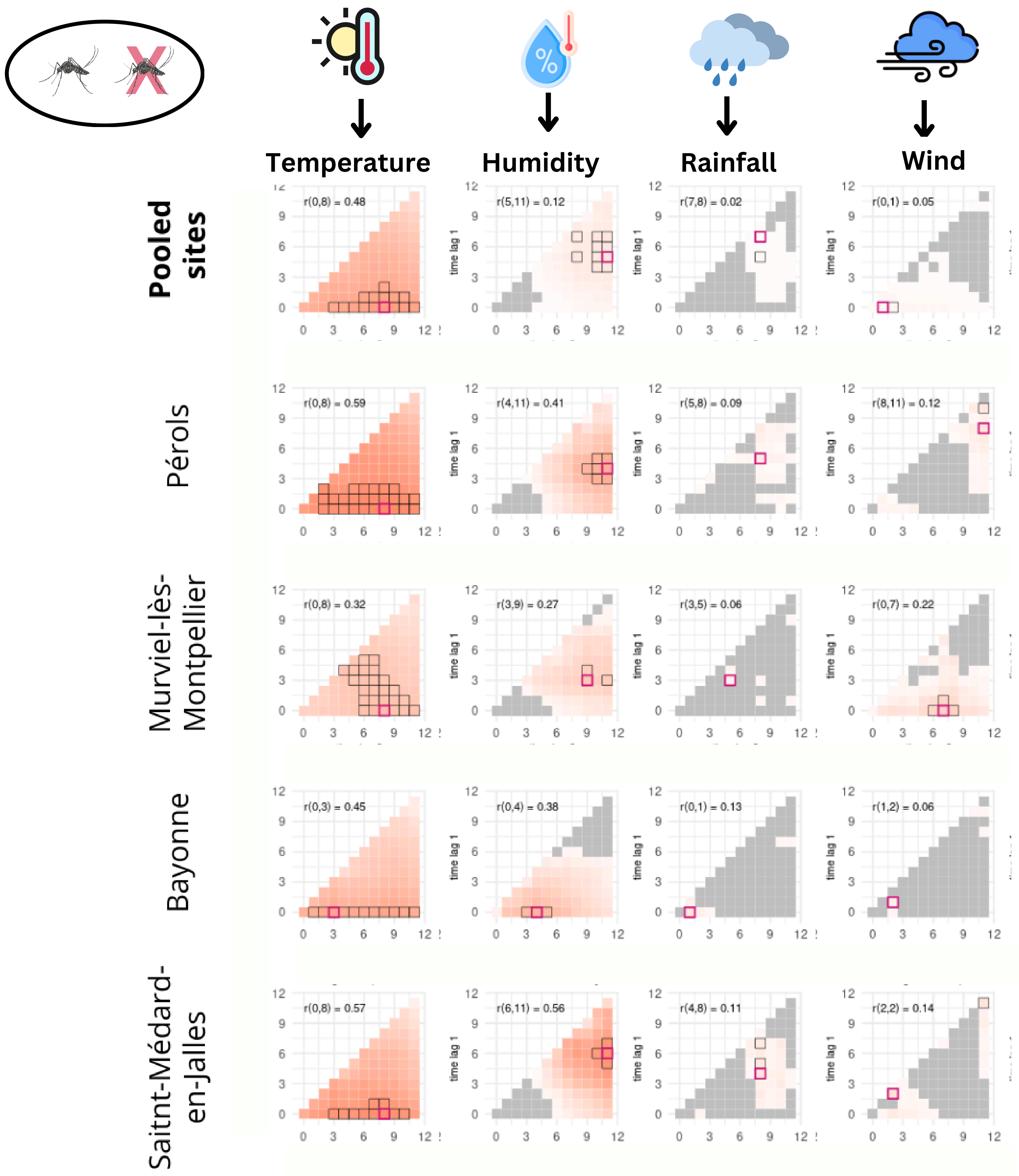


Cross-correlation maps

***Ae. Albopictus* <u>presence</u> ~ weather variables**



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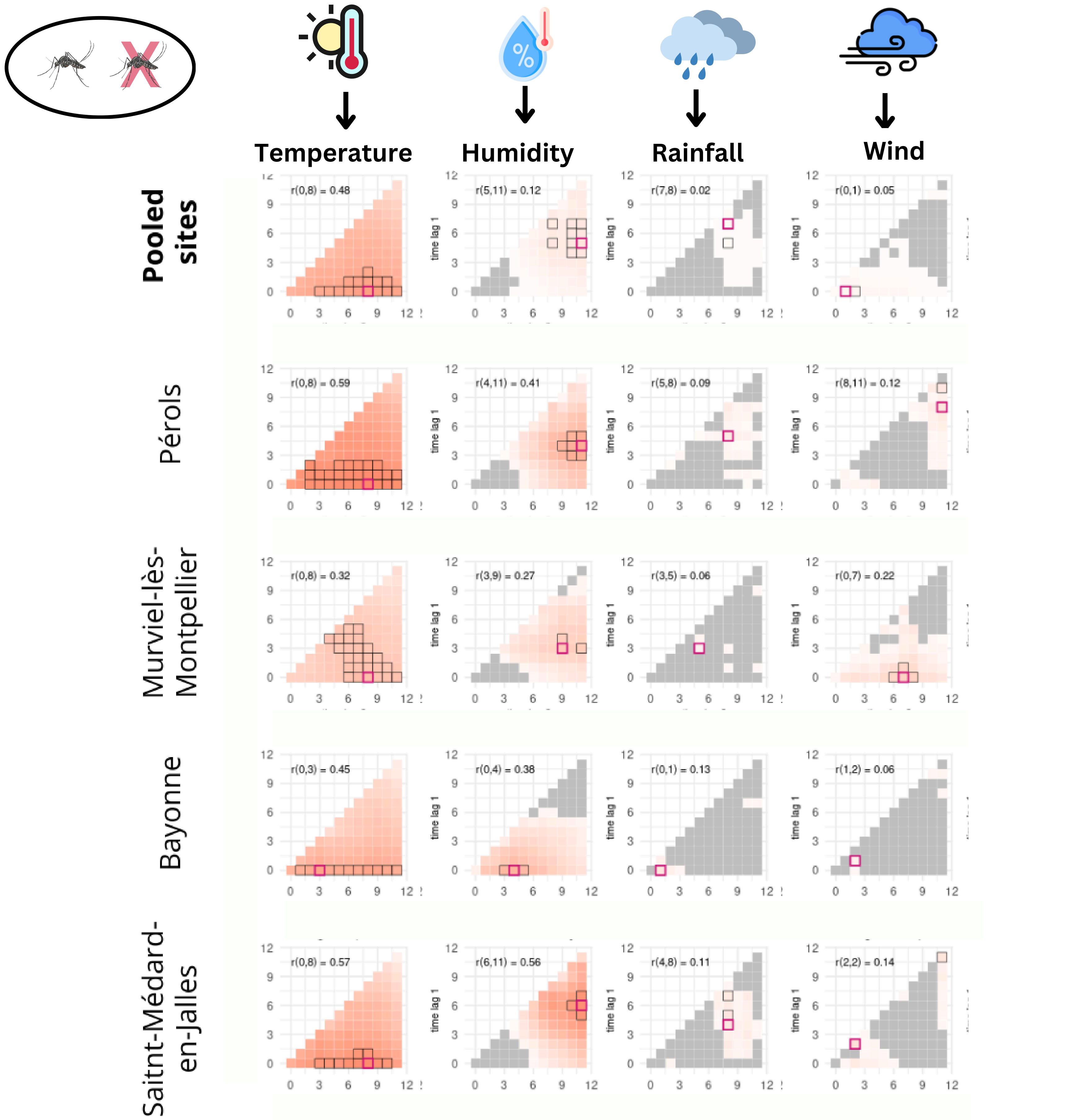
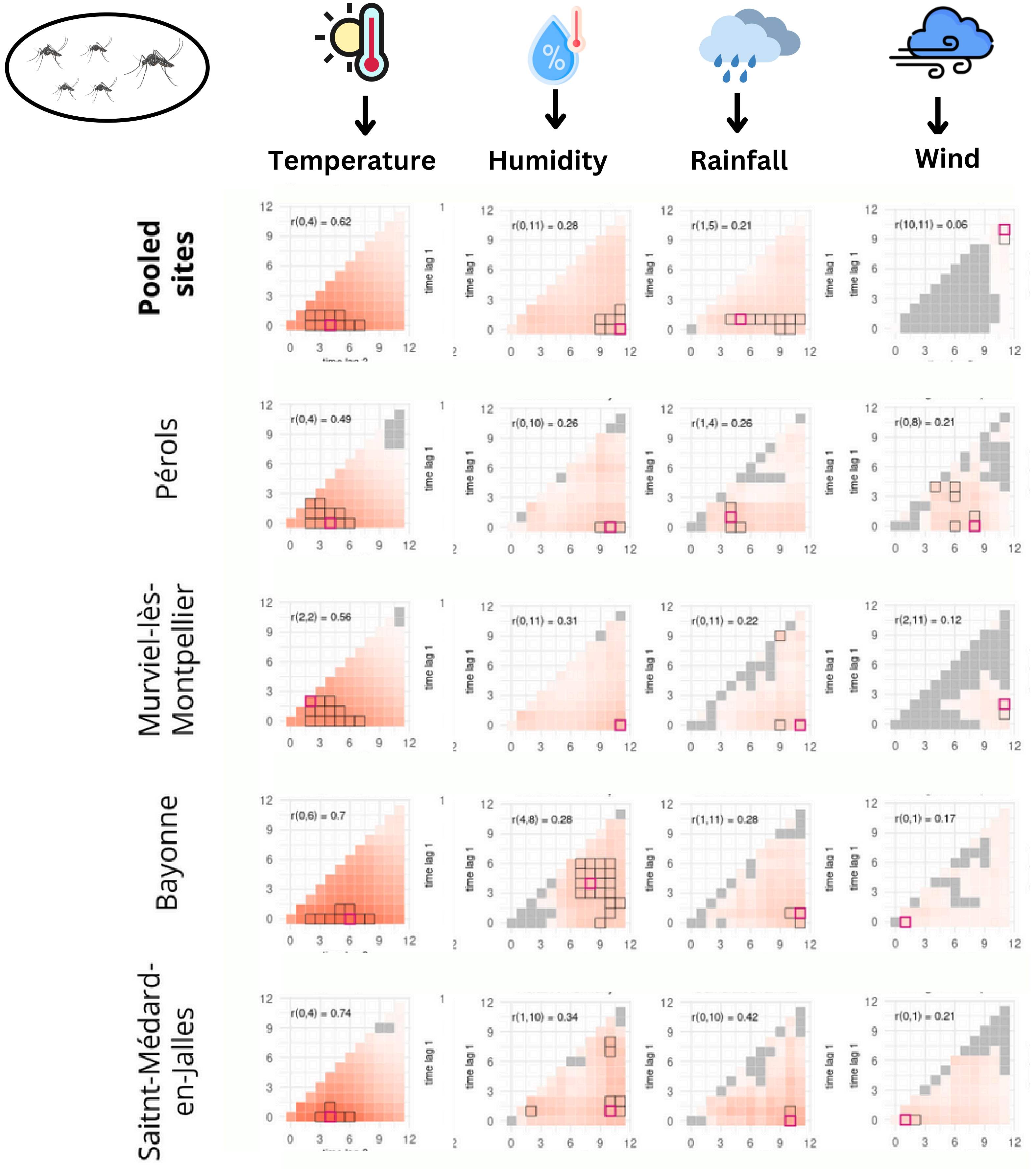
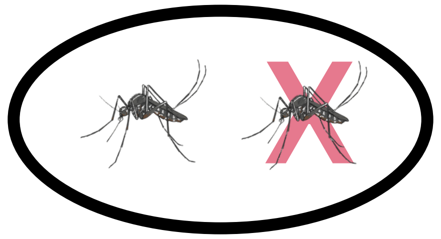


Ae. Albopictus abundance ~ weather variables



Weather variables retained for modeling

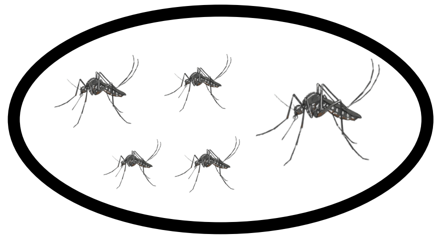
Presence/absence model



> **Average temperature between 0 and 8 weeks** preceding collections

> **Humidity between 5 and 11 weeks** preceding collections

Abundance model



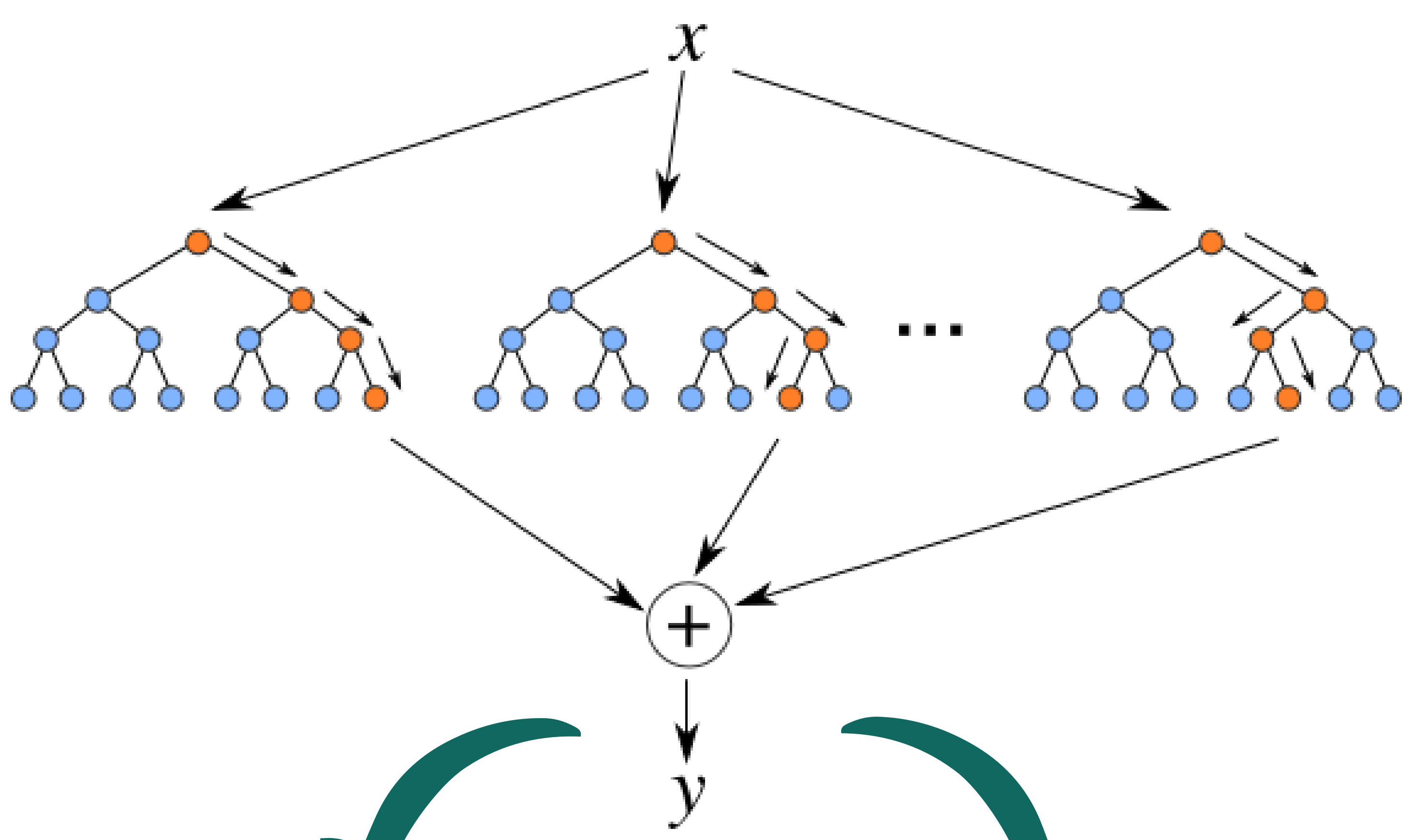
> **Average temperature between 0 and 4 weeks** preceding collections

> **Humidity between 0 and 11 weeks** preceding collections

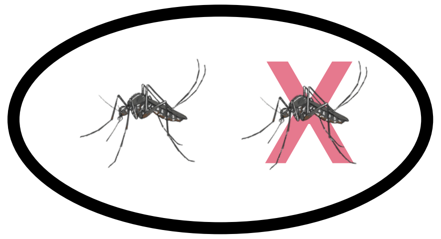
> **Cumulated rainfall between 1 and 5 weeks** preceding collections

Model construction

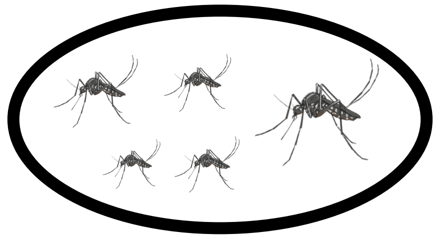
ML approach : Random Forests algorithm



Classification : presence/absence



Regression : abundance



Spatial evaluation

Leave-Site-Out Cross-Validation (CV)

Meyer et al., 2018. Environmental Modelling & Software

Model recursively trained on all sites except one, and evaluated on the left-out site

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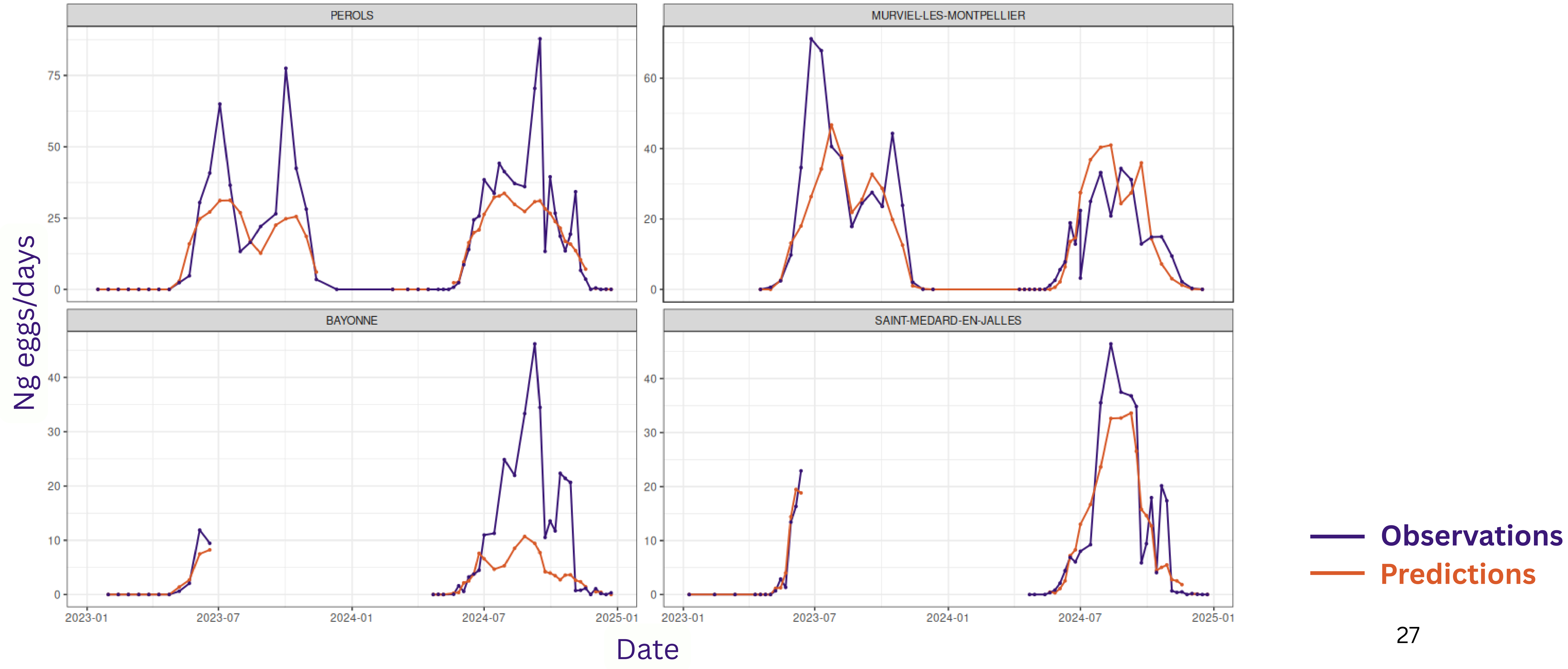
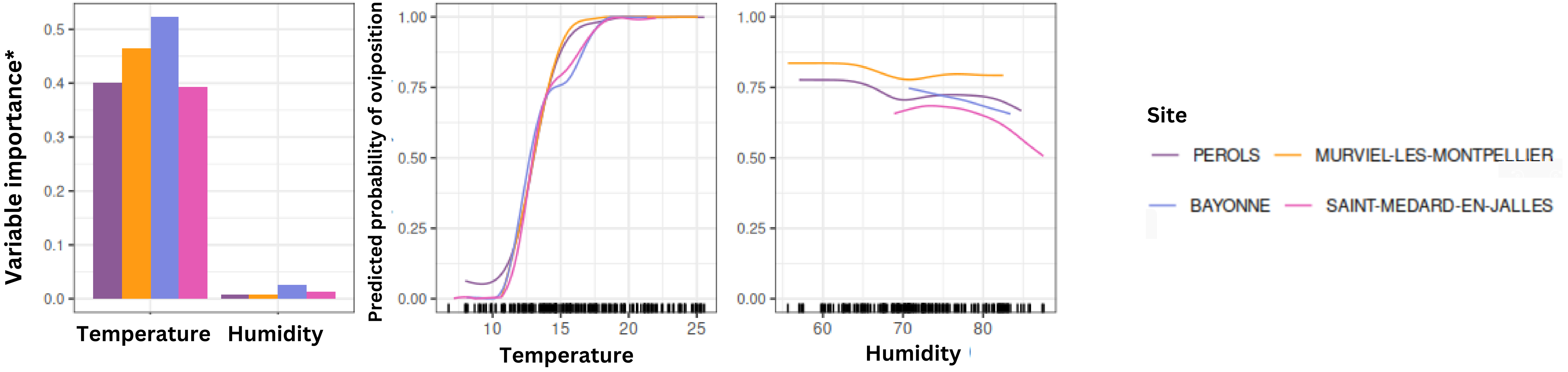


Explainable Machine Learning : global analysis

Presence/Absence



*Importance = mean decrease in accuracy when variable is permuted

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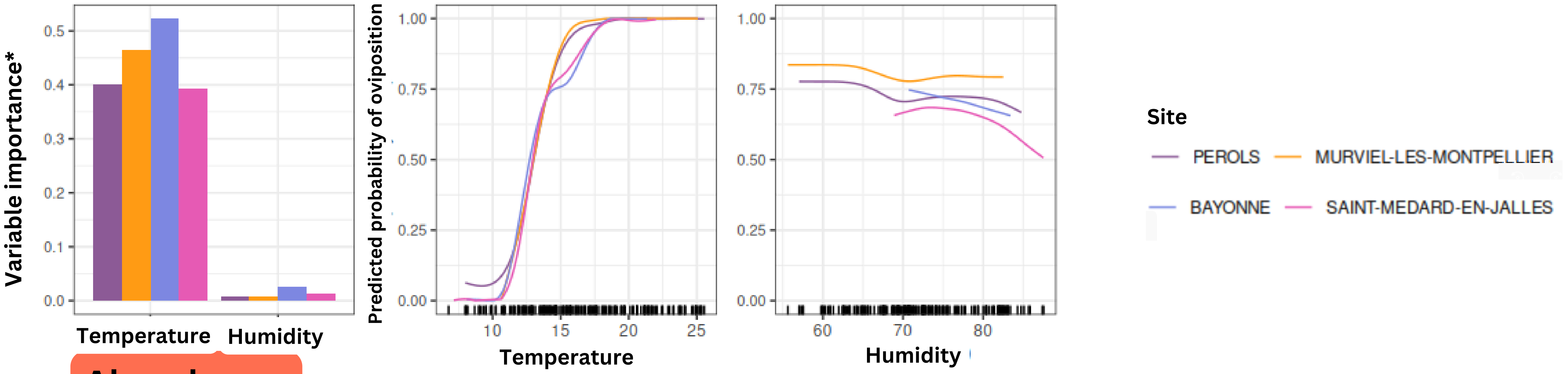

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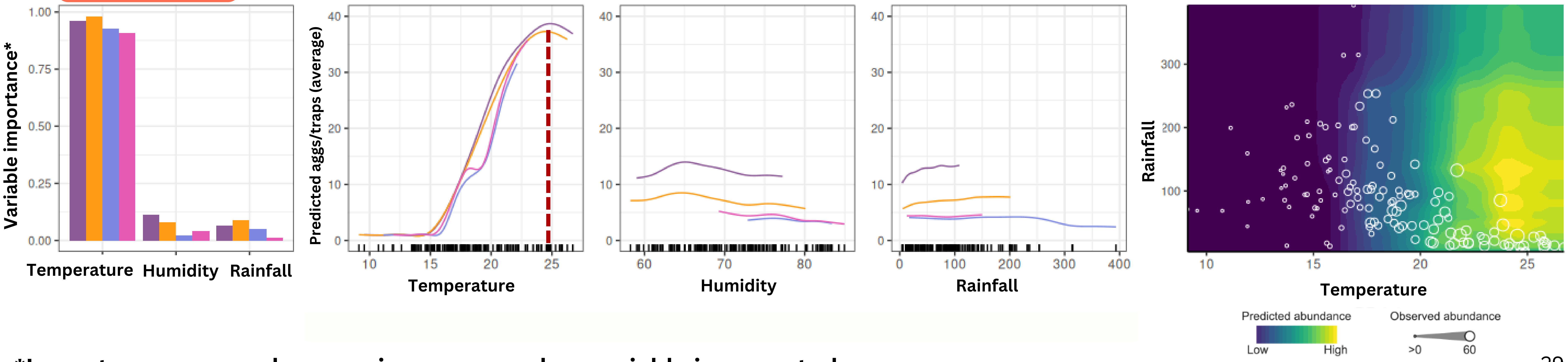

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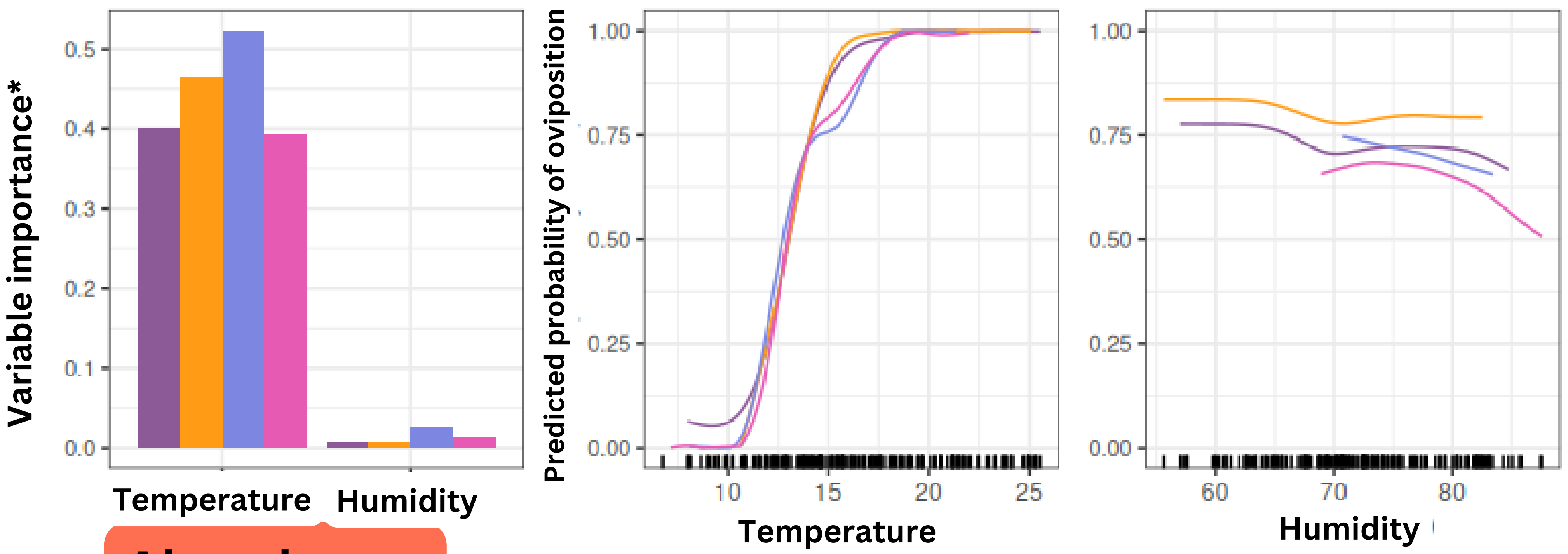
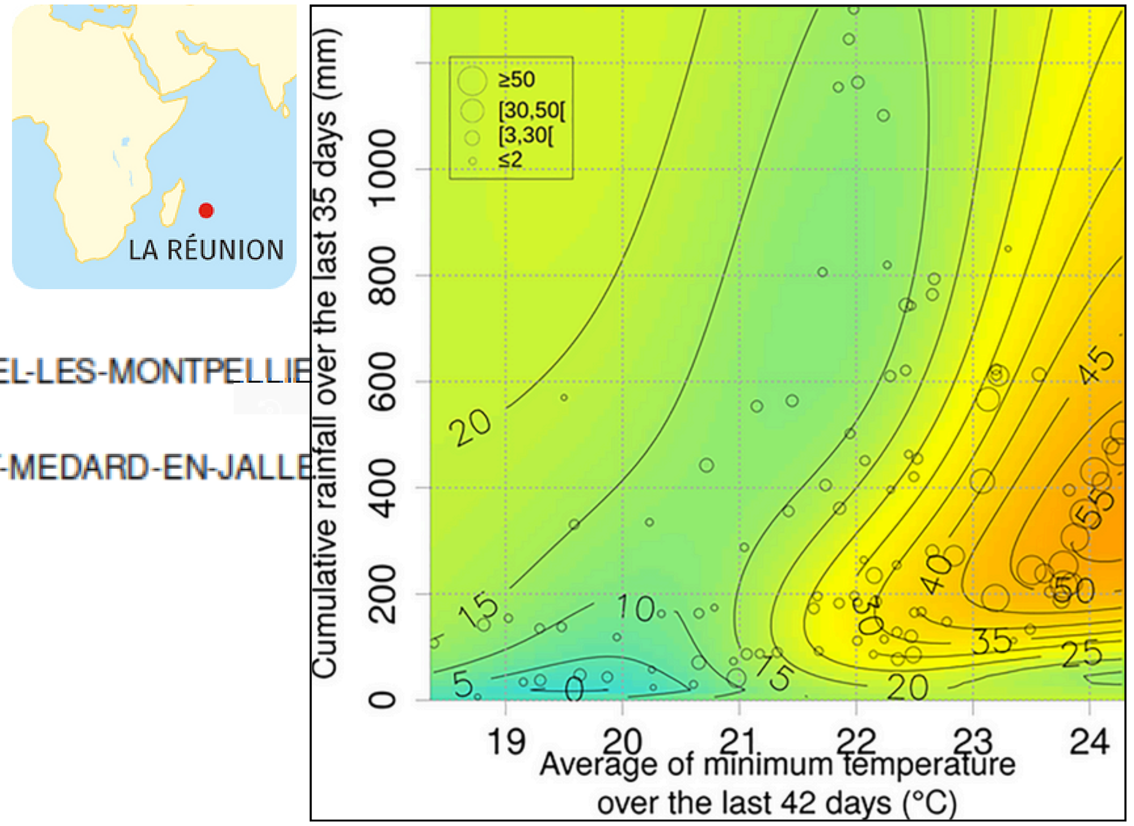


Tran et al., 2020



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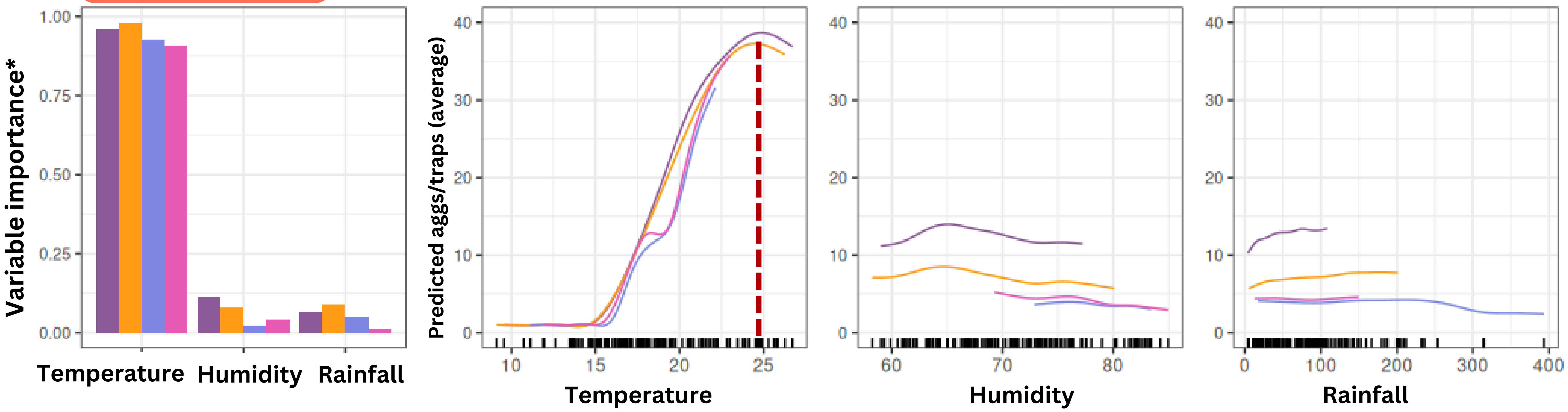

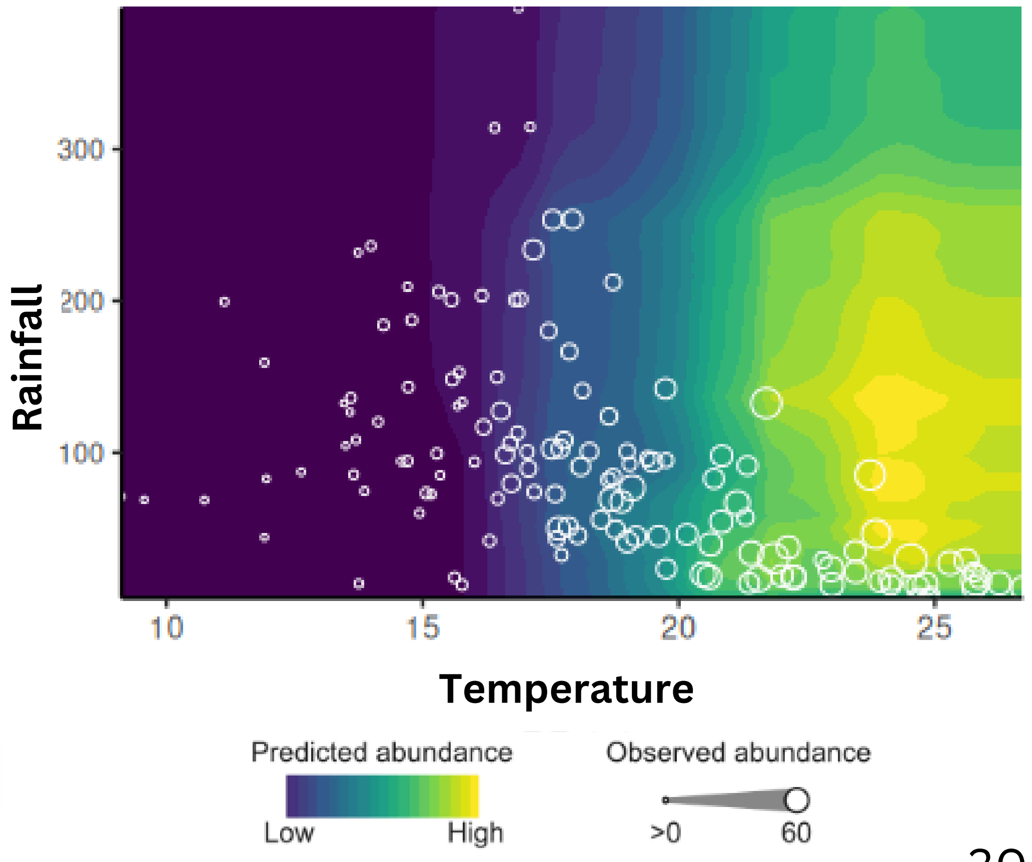

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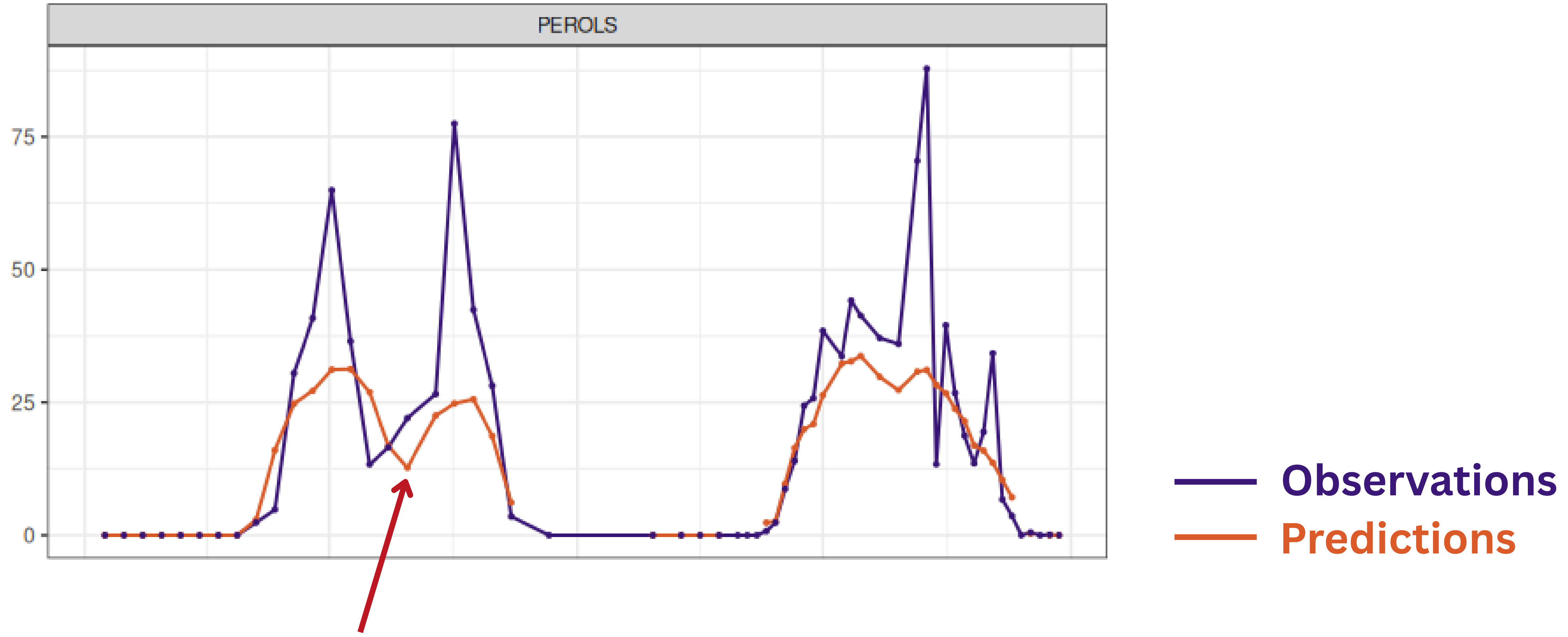
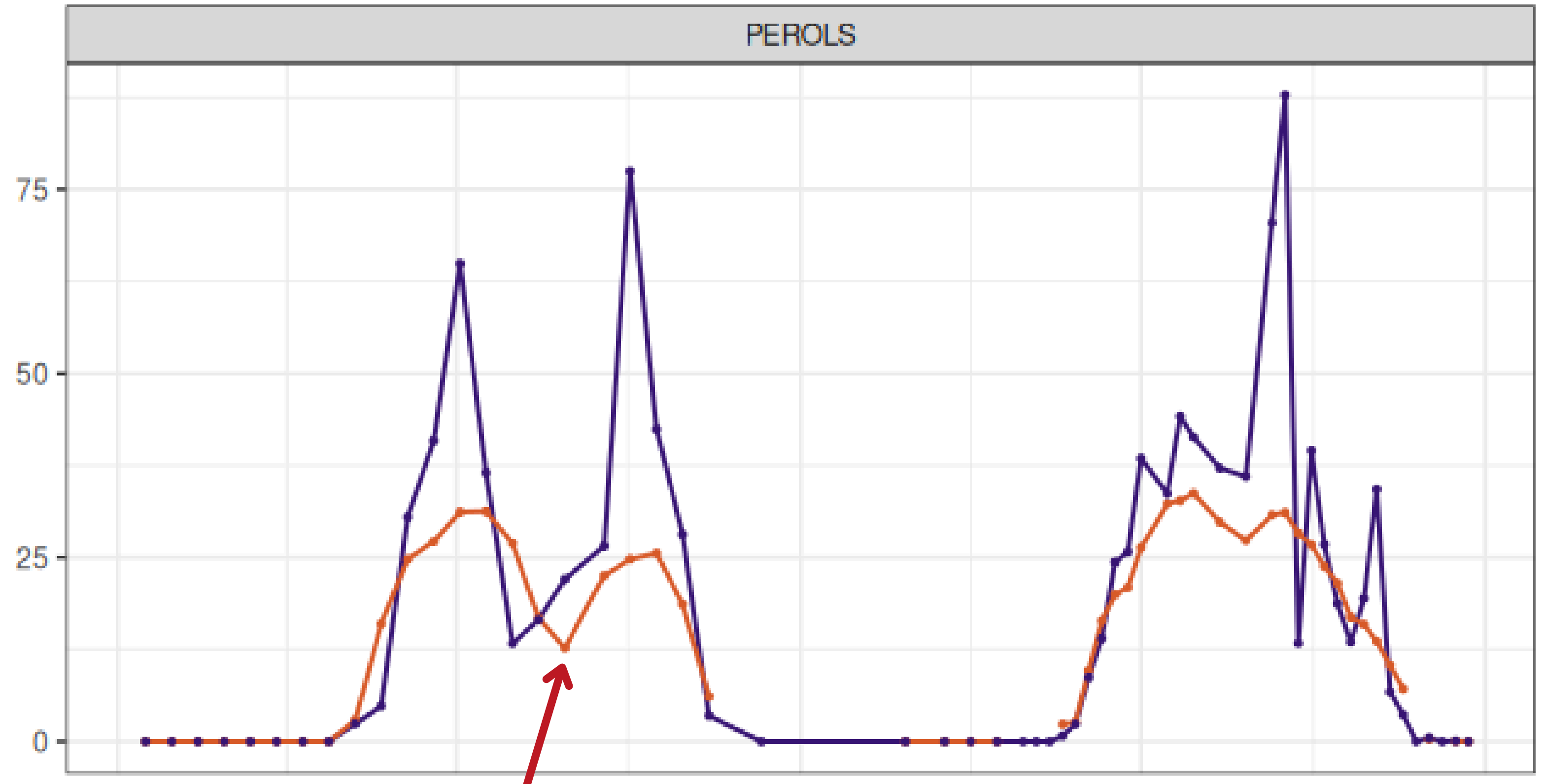
Explainable Machine Learning : local analysis



Why did the model predict this specific value ?

Explainable Machine Learning : local analysis



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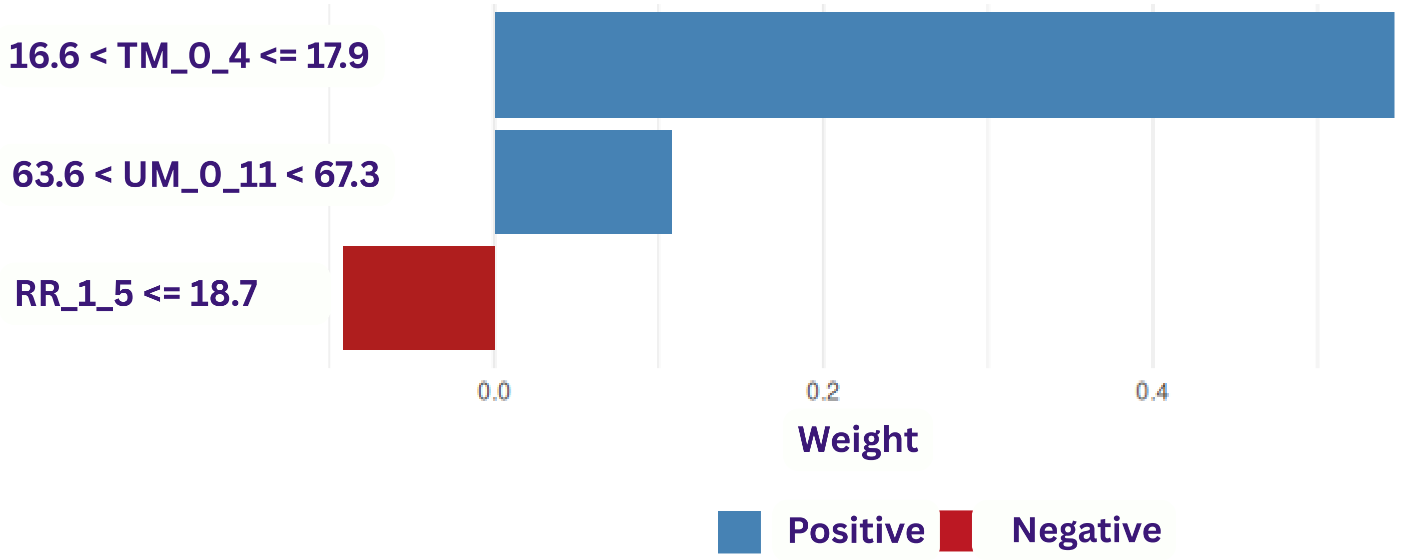
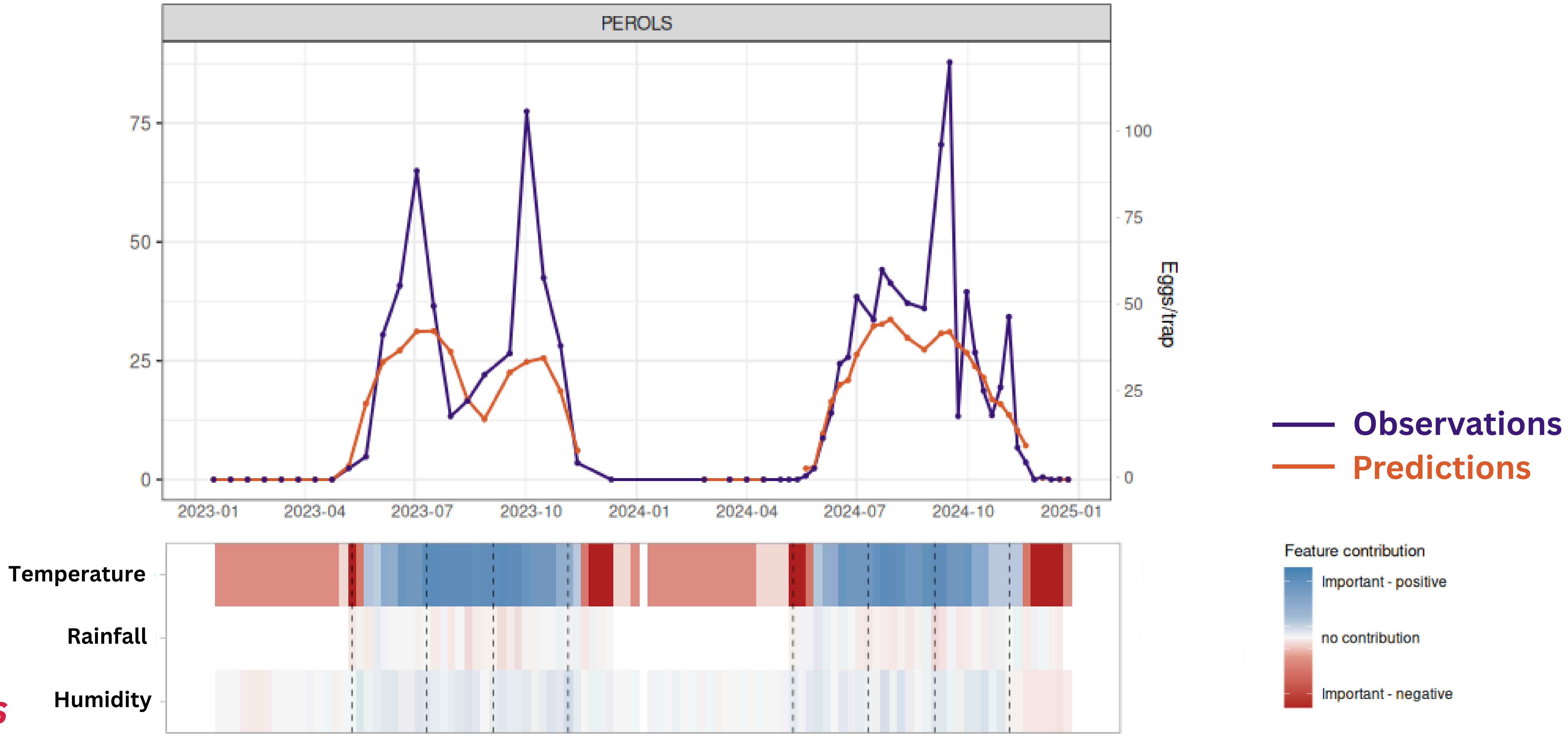
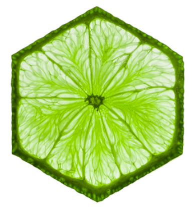


LIME analysis

Ribeiro et al., 2016 “Why Should I Trust You?": Explaining the Predictions of Any Classifier.”

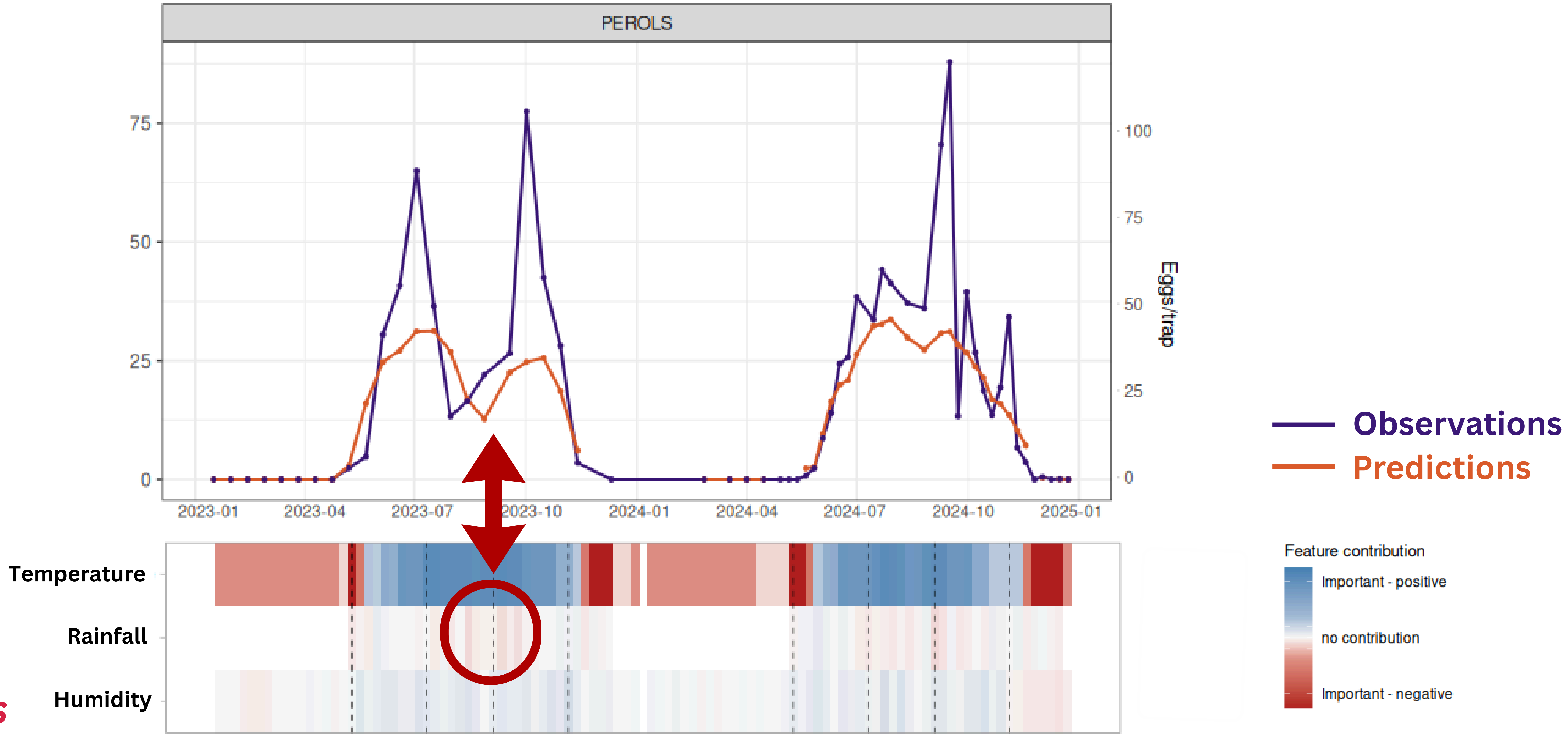
Explainable Machine Learning : local analysis





LIME analysis

Explainable Machine Learning : local analysis

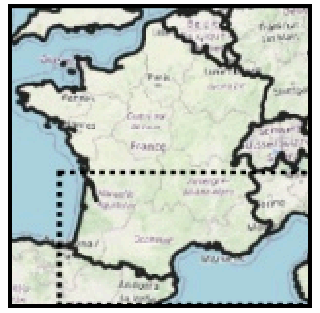


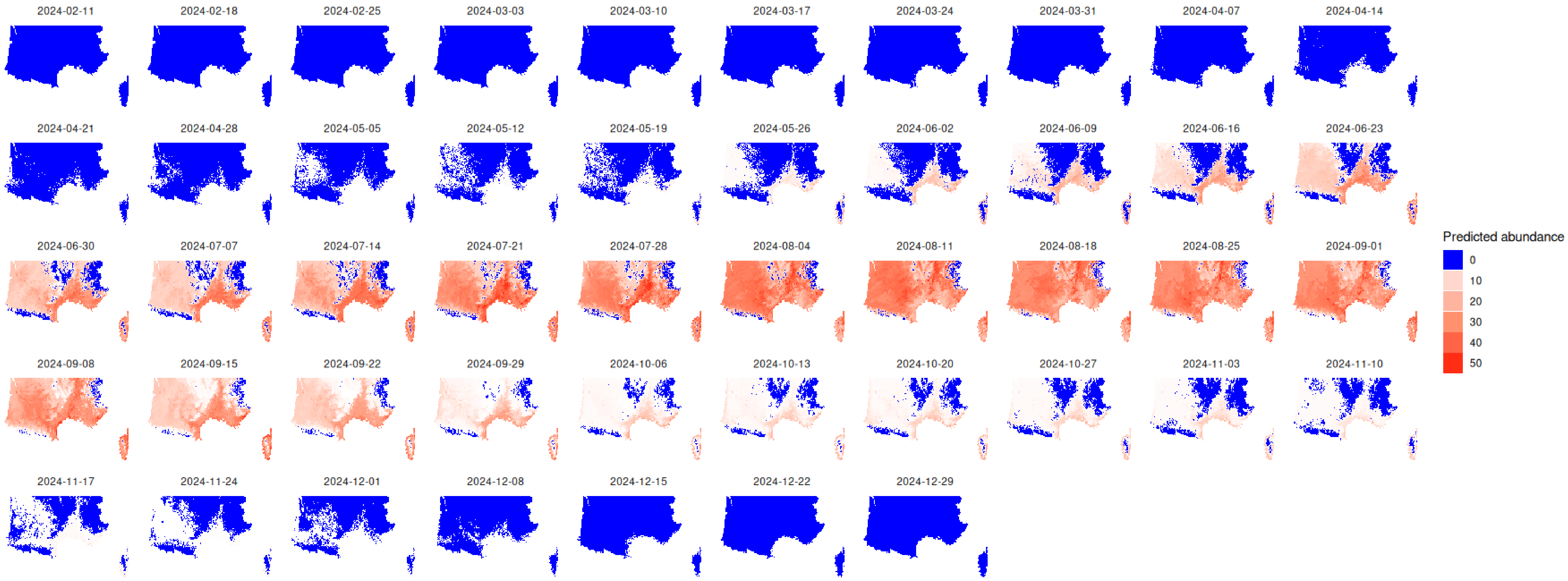
LIME analysis

According to the model,
<u>very few rainfall</u> seems to explain this low point in 2023 (rather than high temperatures)

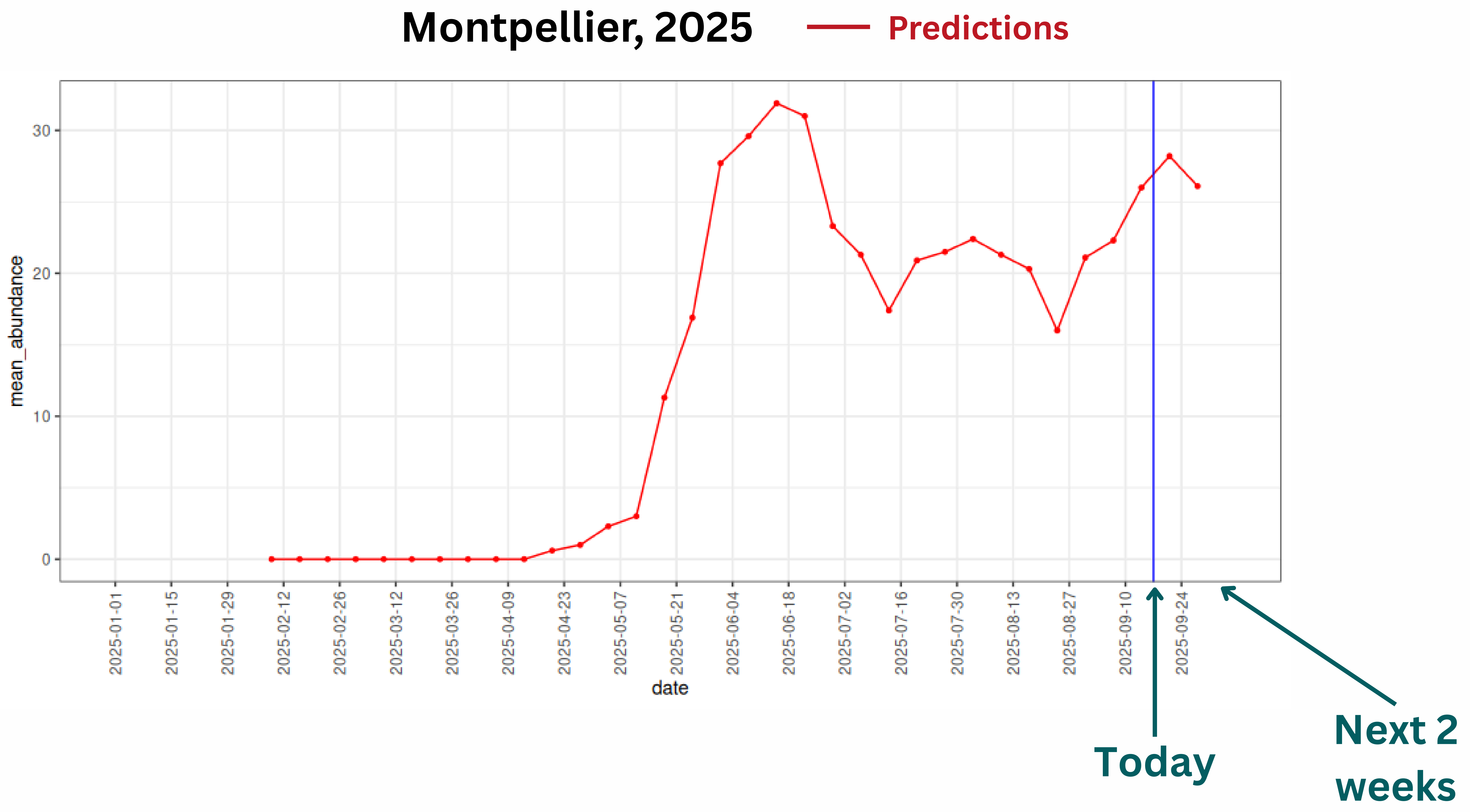
Spatio-temporal predictions

Year 2024 : 5 km resolution - 1 week time frame



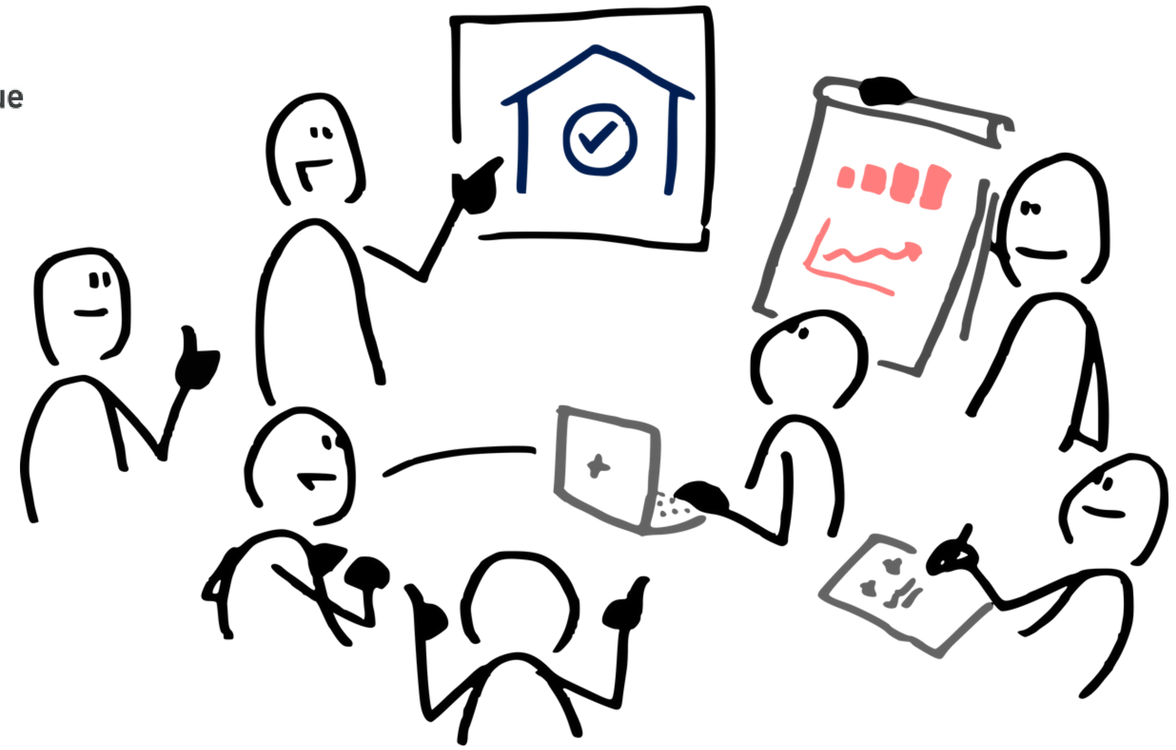


Forecasting



Prospects : Model operationalization

November 2025 : Workshop with stakeholders
(Public health authorities, Vector-control operators, Local political officials, Urban management services)



> Which information ?
> Which spatial scale(s) ?
> Which update frequency ?
> ...

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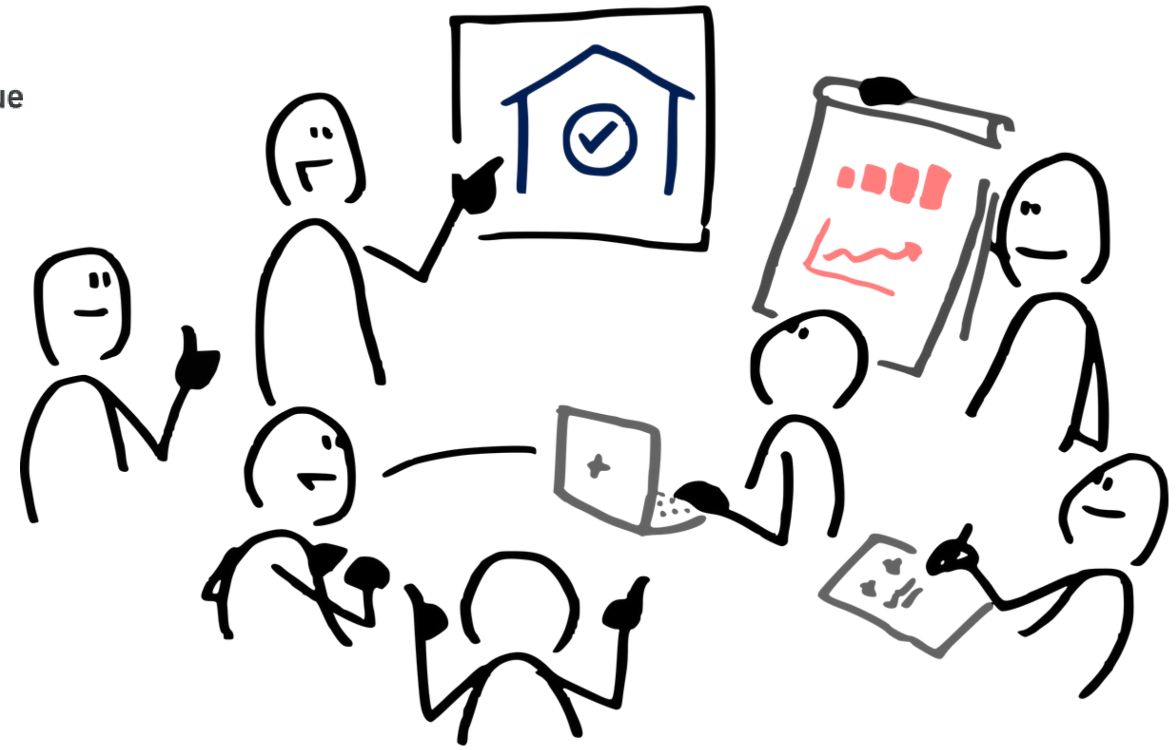

> Which information ?
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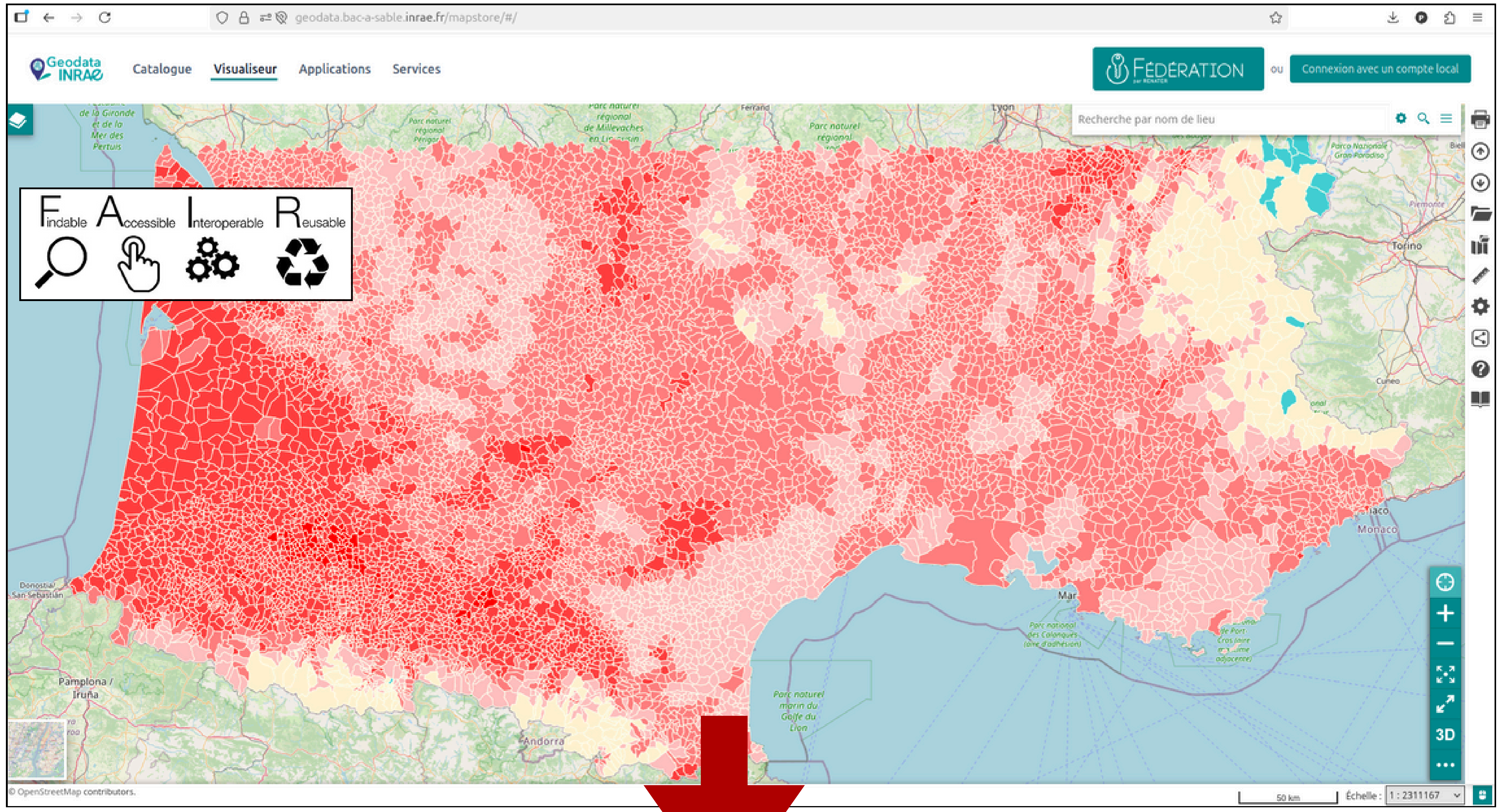
> Which update frequency ?
> ...

User-friendly data portal with real-time predictions



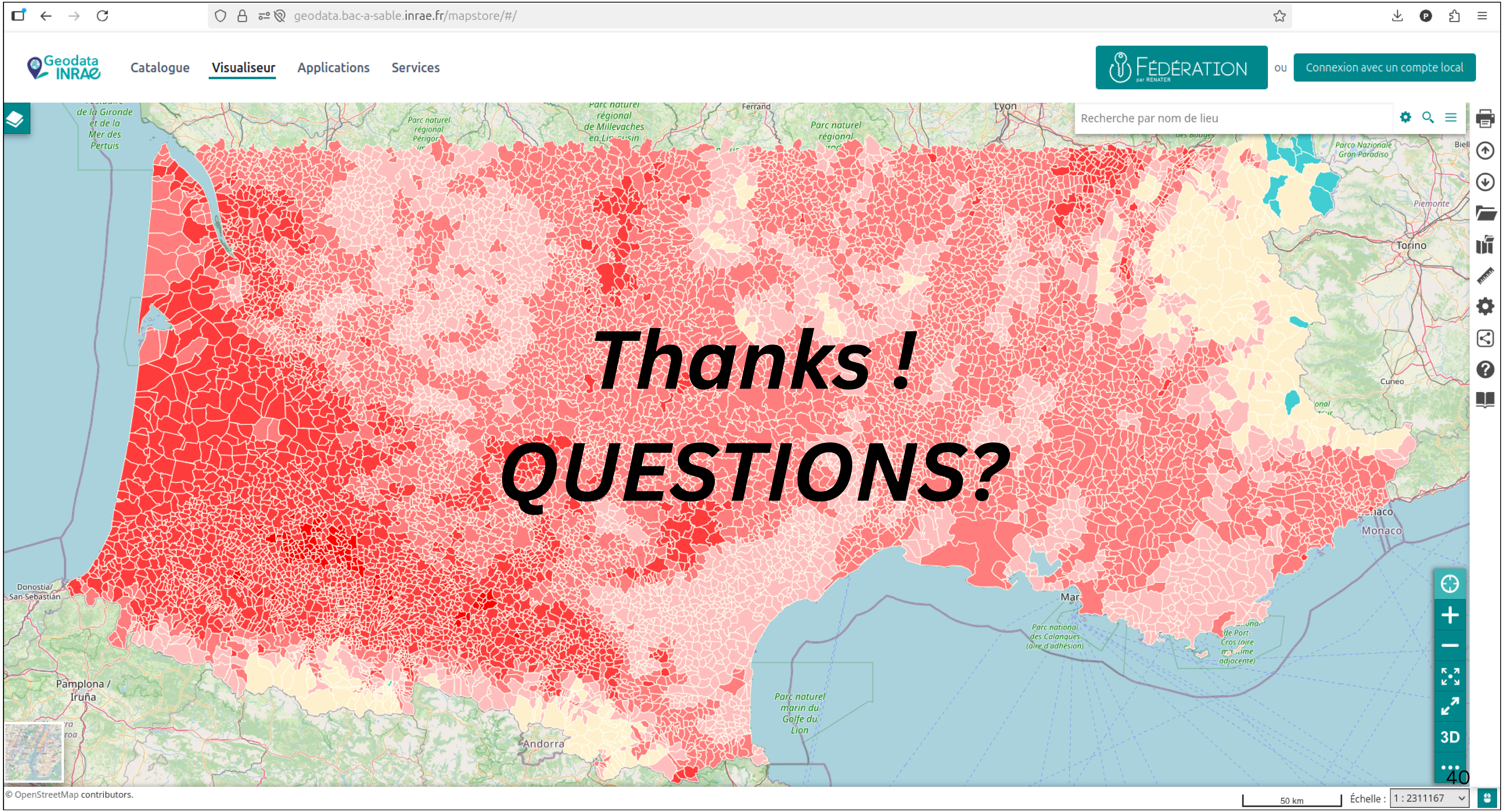
Concluding remarks : AI for surveillance of vectors

> AI enables to build high performing models of vectors dynamics => mainly thanks to its ability to capture complex, possibly hypothesized associations in the data

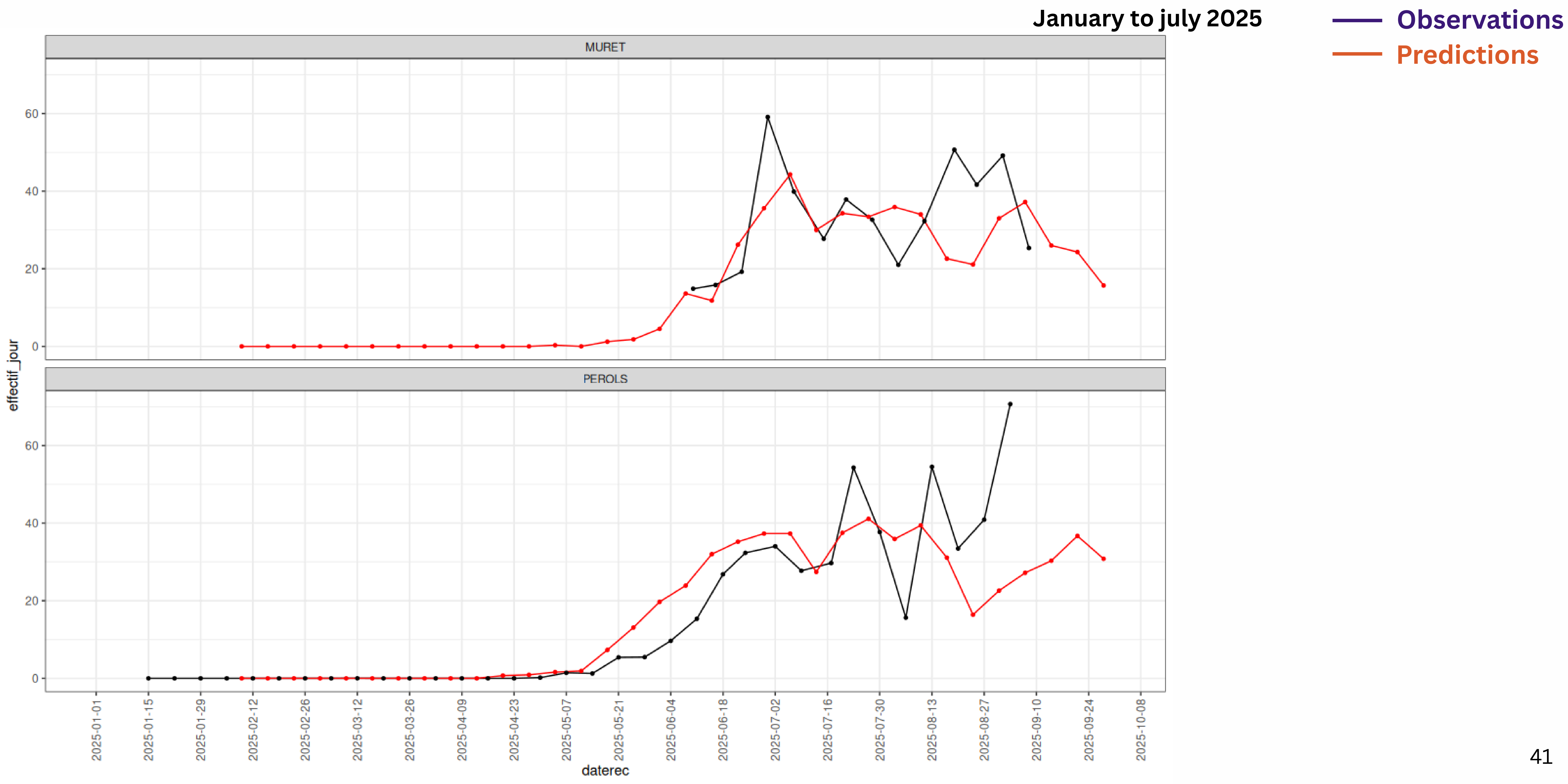
> Interpretable AI enables to understand the behavior of the model ("Why did the model predict this value ?") both globally and locally, providing interesting insights on the vector-environment association

> Need for <u>long-term field surveillance data</u> to build and improve such powerful models

> Need for <u>collaboration</u> beyond modelers and entomologists to build useful and used end-user science-decision tools


geodata.bac-a-sable.inrae.fr/mapstore/#/
Geodata INRAE
Catalogue
Visualiseur
Applications
Services
FÉDÉRATION
par RENATER
ou
Connexion avec un compte local
Recherche par nom de lieu
Thanks !
QUESTIONS?
Torino
Cuneo
Monaco
Andorra
Pamplona / Iruña
Donostia/ San Sebastián
Parc naturel marin du Golfe du Lion
Parc national des Calanques (aire d'adhésion)
Parco Nazionale Gran Paradiso
Piemonte
Lyon
3D
© OpenStreetMap contributors.
50 km
Échelle : 1 : 2311167

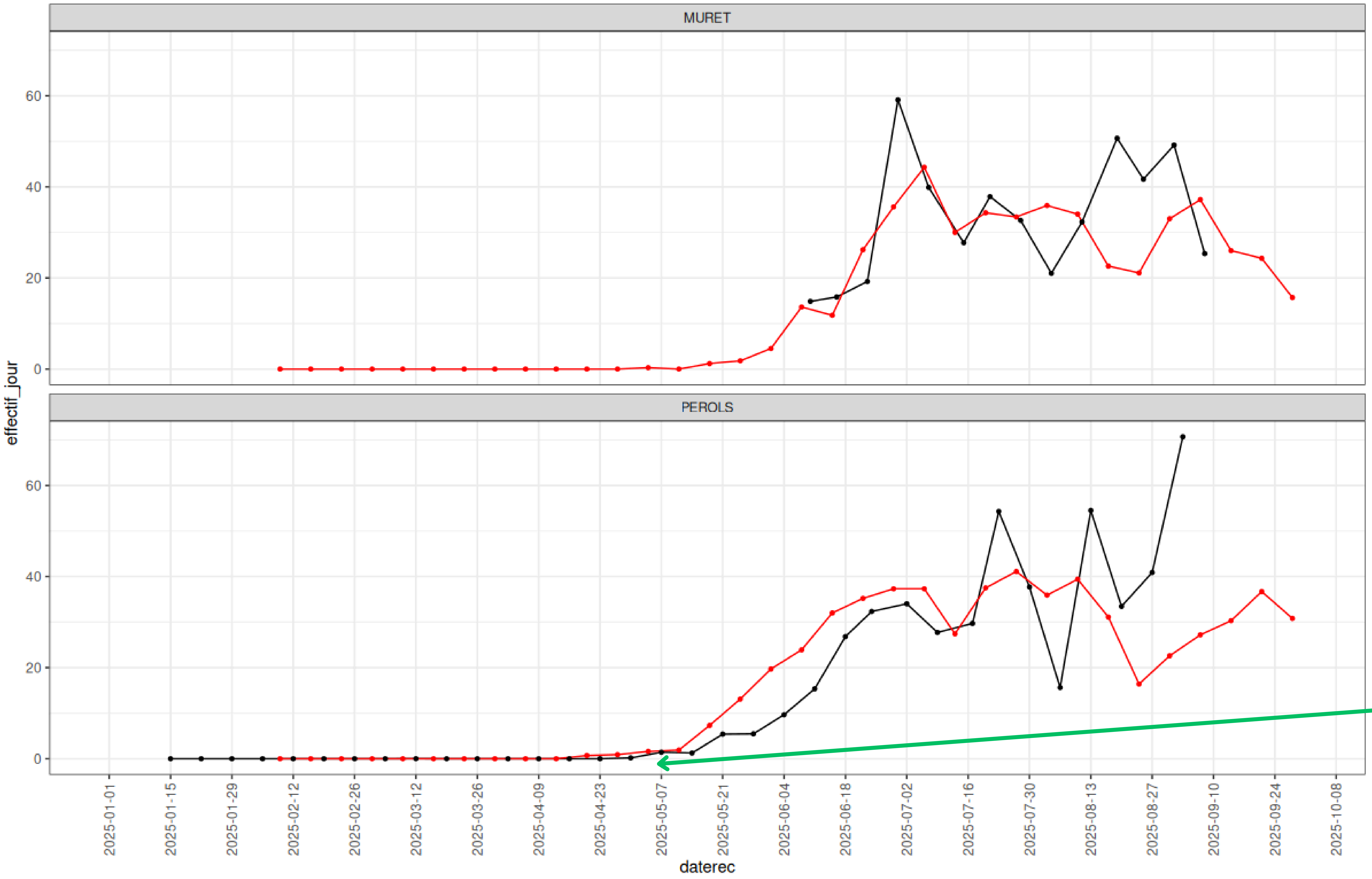
Observations ~ predictions : 2025



Observations ~ predictions : 2025

January to july 2025

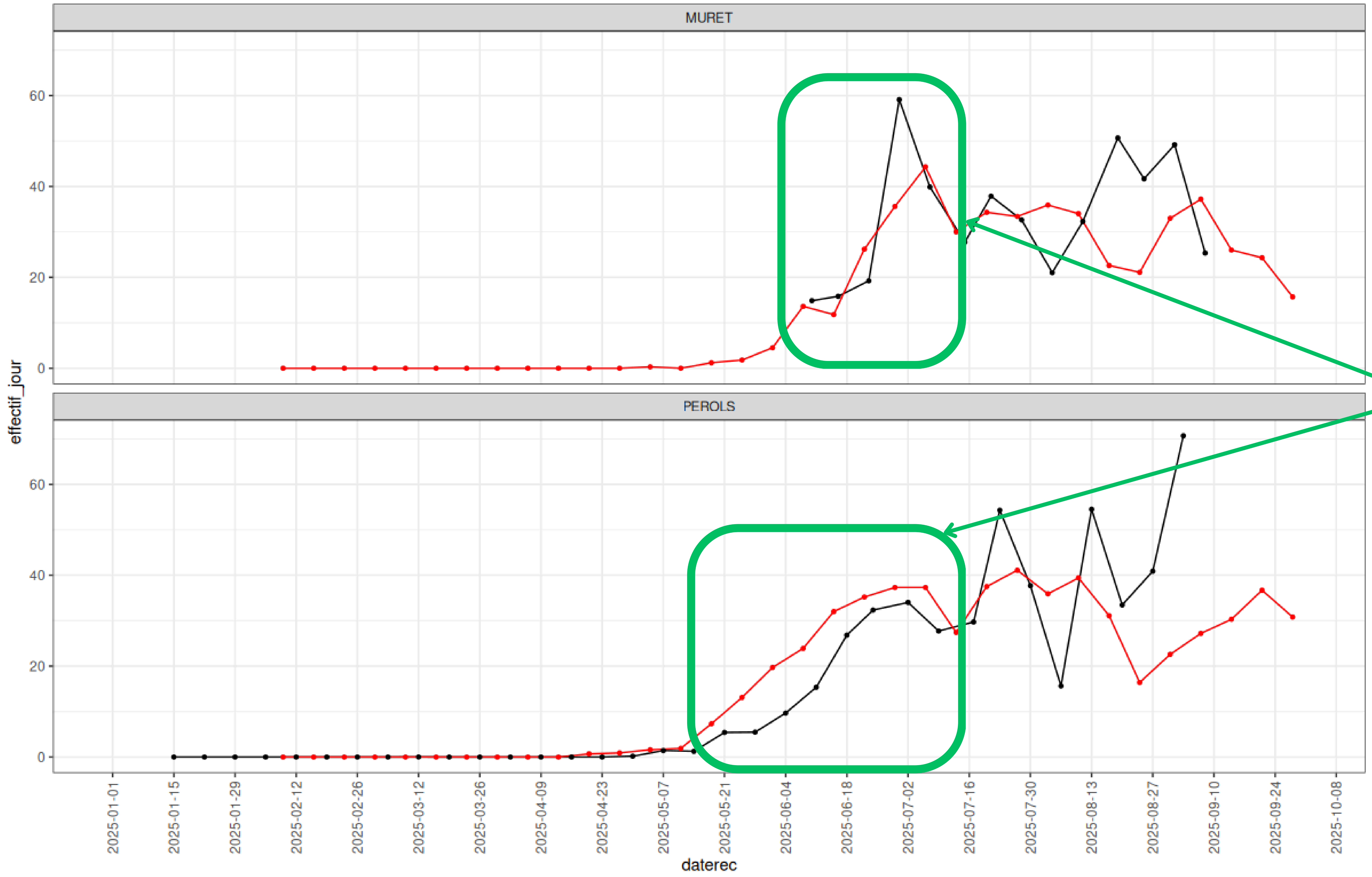
Observations
Predictions



The model predicts very well the start of the entomological season

Observations ~ predictions : 2025

January to july 2025

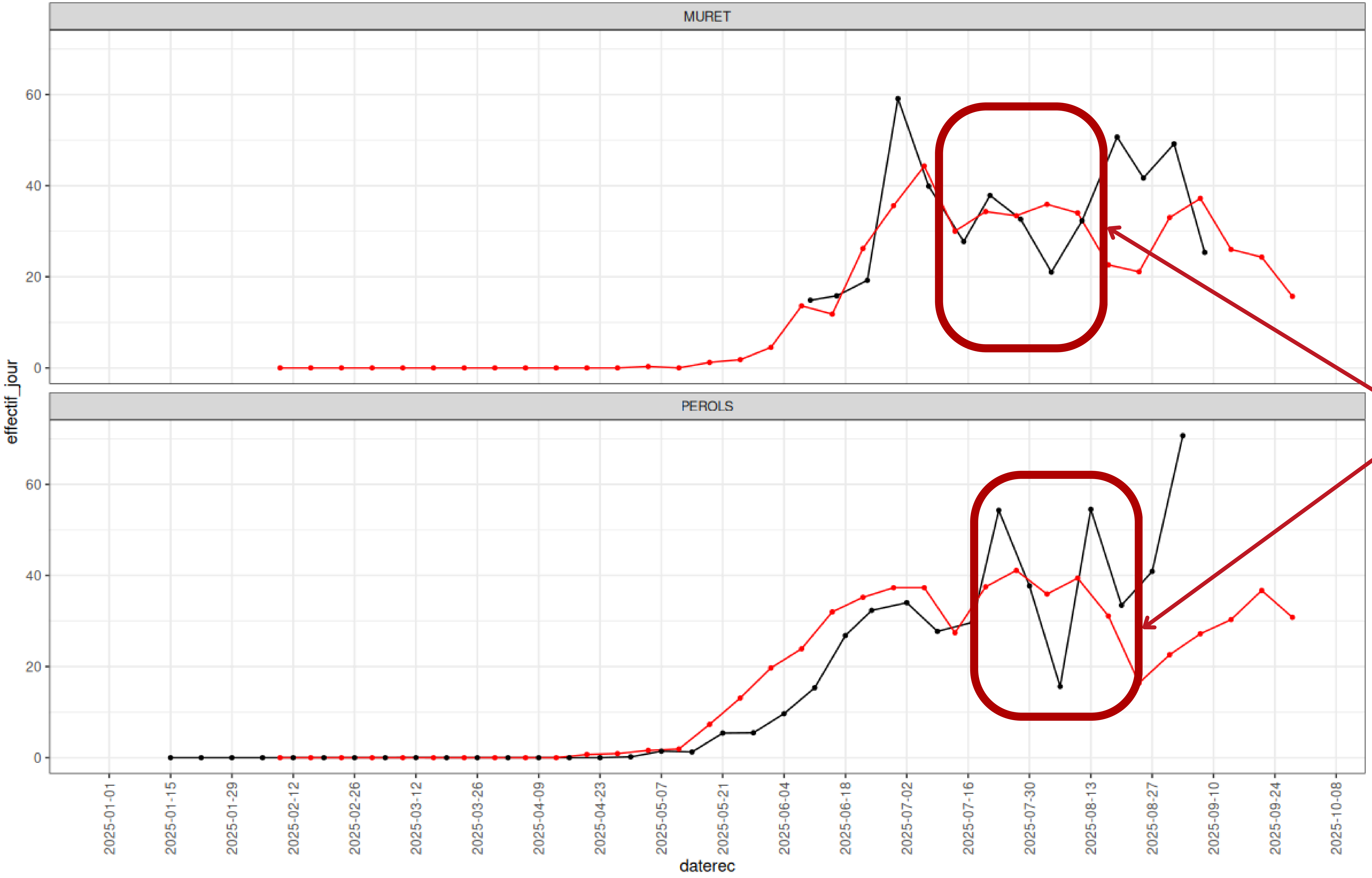


Observations
Predictions

The model predicts well the first ascent and peak (in july)

2025 : Observations ~ predictions

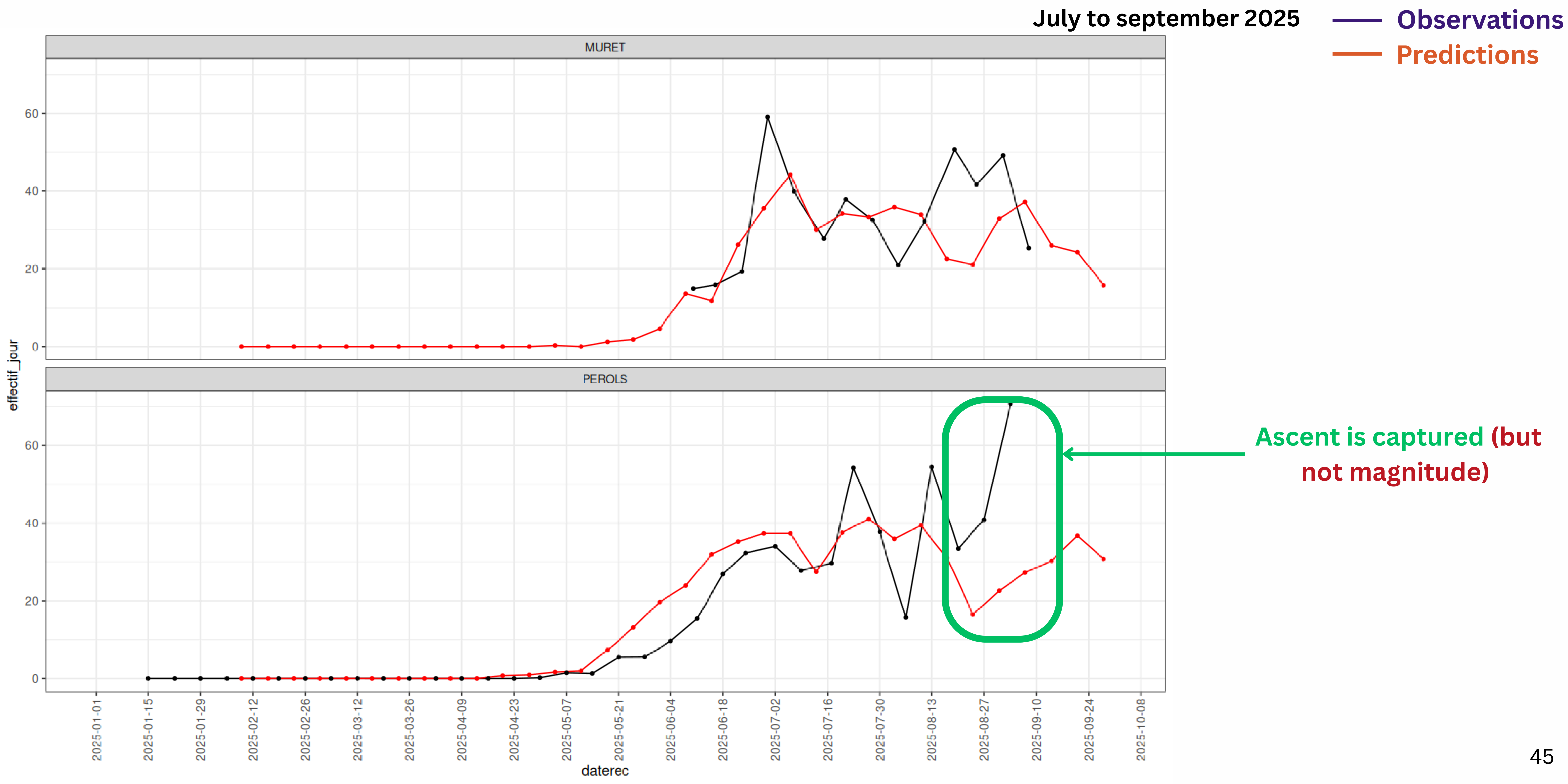
July to september 2025



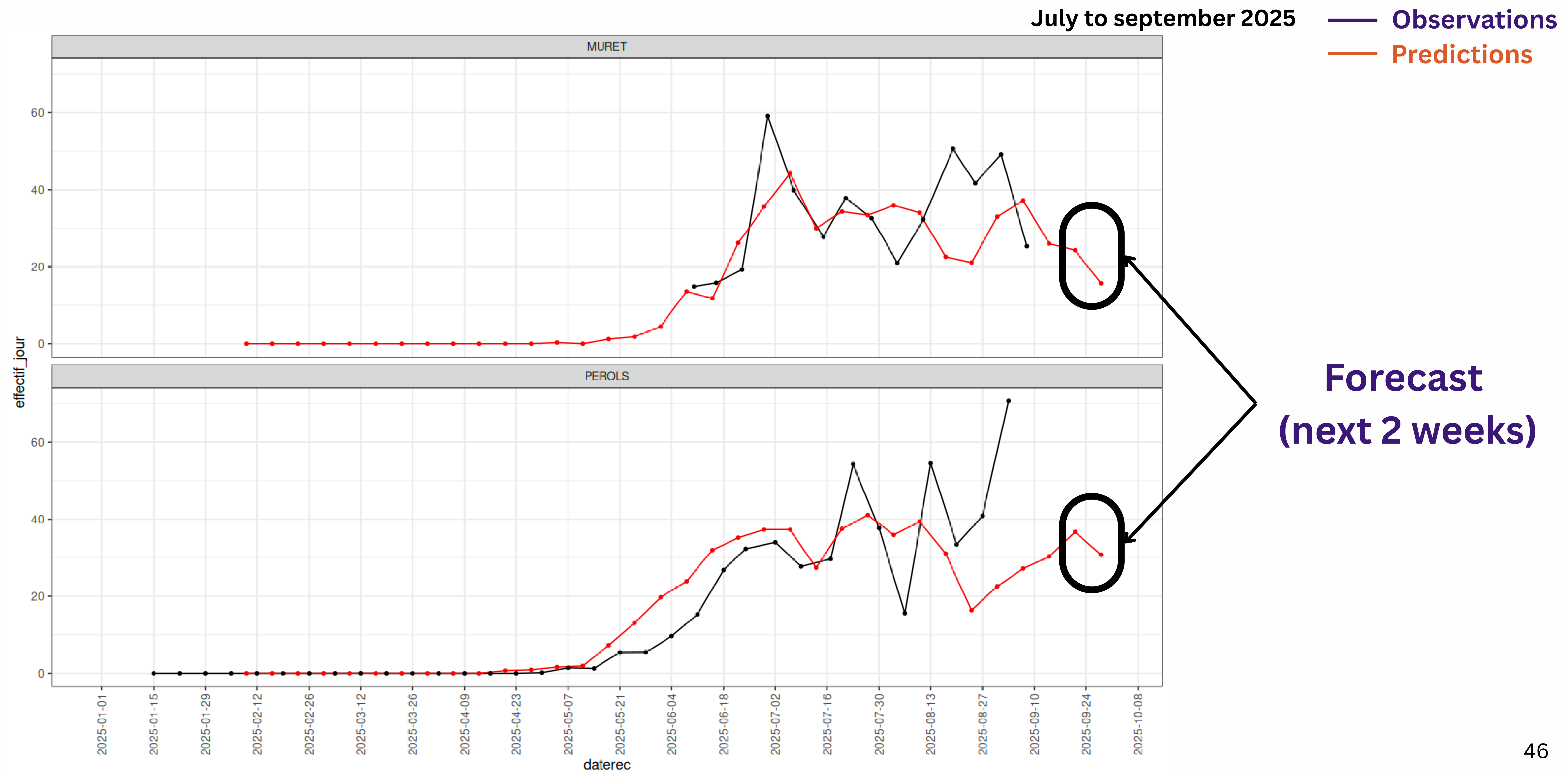
Observations
Predictions

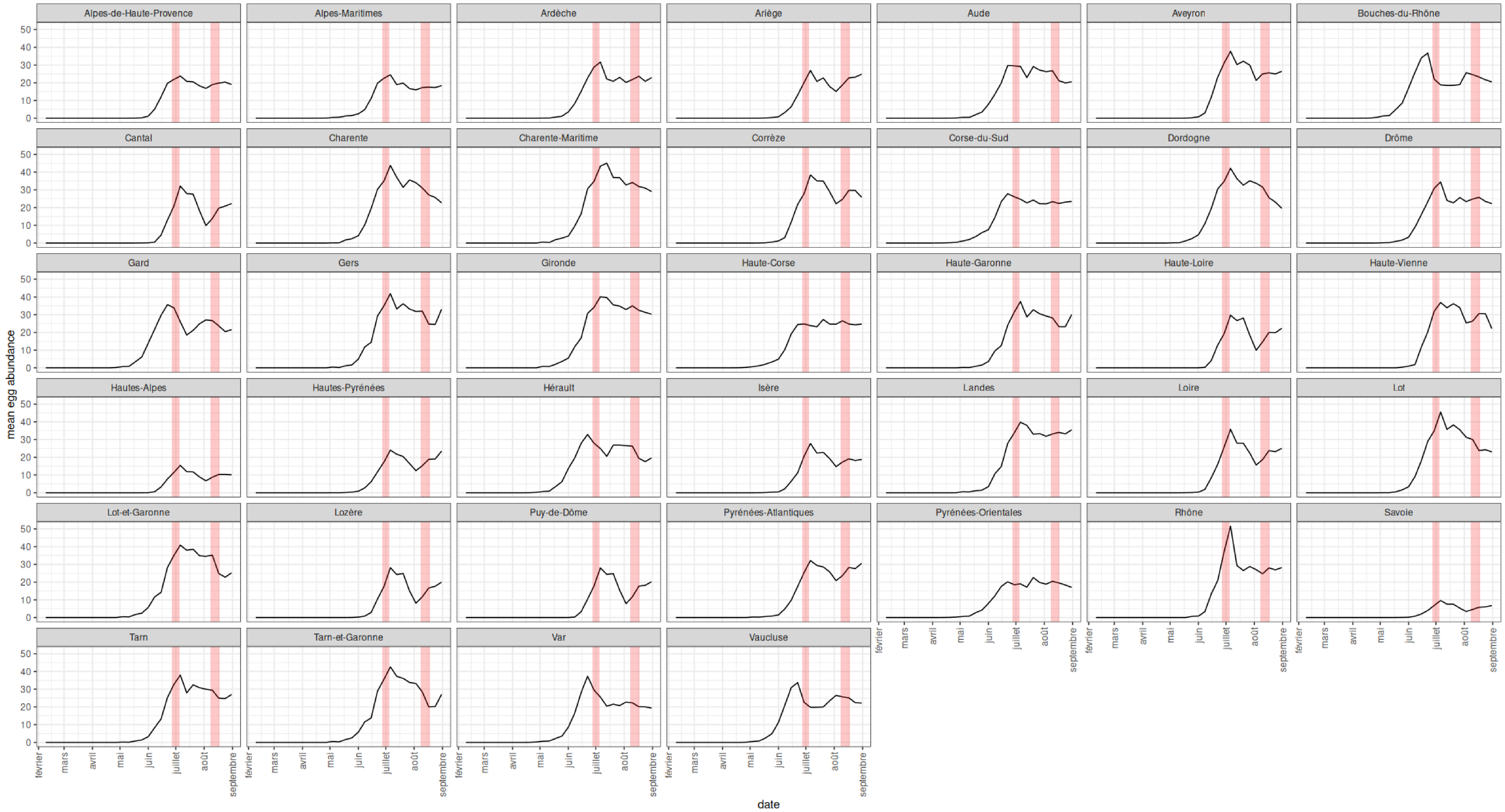
Hardly captures these small-scale variations in July-August

2025 : Observations ~ predictions



2025 : Observations ~ predictions





Alpes-de-Haute-Provence
Alpes-Maritimes
Ardèche
Ariège
Aude
Aveyron
Bouches-du-Rhône
Cantal
Charente
Charente-Maritime
Corrèze
Corse-du-Sud
Dordogne
Drôme
Gard
Gers
Gironde
Haute-Corse
Haute-Garonne
Haute-Loire
Haute-Vienne
Hautes-Alpes
Hautes-Pyrénées
Hérault
Isère
Landes
Loire
Lot
Lot-et-Garonne
Lozère
Puy-de-Dôme
Pyrénées-Atlantiques
Pyrénées-Orientales
Rhône
Savoie
Tarn
Tarn-et-Garonne
Var
Vaucluse
mean egg abundance
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février
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avril
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août
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date